Reliability Implications of Price Responsive Demand: A Study of New England's Power System

by

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ABSTRACT

With restructuring of the traditional, vertically integrated electricity industry come new opportunities for electricity demand to actively participate in electricity markets. Traditional definitions of power system reliability have carried over from the vertically integrated market structure, but this thinking will become increasingly problematic as the proportion of electricity demand responsive to market prices increases. Using New England as an example, this thesis highlights these difficulties by employing a Probabilistic Production Costing model modified to account for price responsive demand. A Neural Gas clustering algorithm is used to deal with the time-varying nature of price responsive demand. We show that neglecting to account for price responsive demand could result in underestimating system reliability by traditional measures, and discuss a possible new metric to help the transition to thinking of reliability as one aspect of whole market performance.

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1 Introduction

Electricity industry structures in much of the United States and around the world have undergone great changes in the past two decades. Until the beginning of the 1990s, the activity of electricity generation was grouped with transmission and distribution and undertaken primarily by large, vertically integrated utilities subject to regulatory oversight. Under this paradigm, ensuring an adequate supply of generation was the responsibility of a single entity, the utility, overseen by regulators.

The Public Utility Regulatory Policies Act (PURPA), passed in 1978 by the United States Congress as part of the National Energy Act, was the first step in a new direction. PURPA was followed by the reform implemented in the mid-1980s in Chile, and more intensive reforms implemented in the UK, Norway and others in the 1990s. Backed by solid theoretical foundations (Joskow & Schmalensee, 1983) (Schweppe, Caramanis, Tabors, & Bohn, 1988), these reforms changed the conventional wisdom about the regulated utility industry. A significant number of power systems began to gradually experiment with the process often dubbed "liberalization" or "deregulation".

Though implementations varied greatly, the main thrust of the changes has been to give multiple generation companies the opportunity to compete with one another in wholesale electricity markets. Some systems have decided to fully liberalize the retail market[1] as well (mostly in Europe rather than the U.S.), while others have remained under the regulated framework, in which regulated distribution utilities purchase energy on behalf of retail customers. Figure 1 illustrates the change in industry structure as a result of deregulation (note that in New England, retail has not been deregulated as in Europe).

[1] The main meaning of a full liberalization of the retail market is that the regulator no longer determines the price for energy. In the case of full retail market liberalization, the regulator's role is limited to supervision of the wholesale market to assure competition levels are adequate, to design the network access tariffs, and to defray regulated costs (transmission, distribution, system operation and others such as subsidies for renewables).

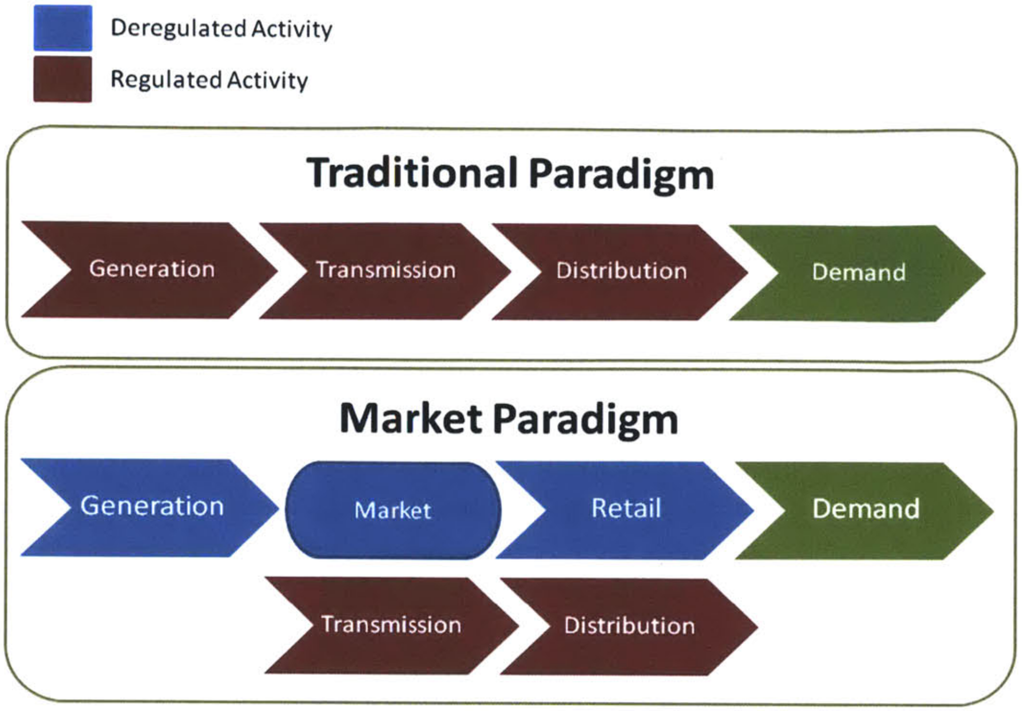

Figure 1: Change in structure of electricity industry as a result of deregulation

While the process is called 'deregulation', in fact the role of the regulator in liberalized power systems is no less important and complex than under the previous system (Borenstein & Bushnell, 2000). Where before regulators had only to deal with a single utility to ensure system reliability, now a whole host of generation companies interacting with retailers (regulated or not) and system operators collectively determine the fate of the power system. While many of the initial challenges in deregulated electricity systems have now been overcome, innovation continues both toward more advanced technical oversight of power systems and better regulatory frameworks for electricity markets.

Originally, an expected key advantage of electric power systems reform was to transfer the decision-making process for capacity expansion to market agents in such a way that the related risks would be borne by these market agents rather than regulated utilities. The idea was that as electricity markets developed, the central planning role of the regulator would decrease. Unfortunately, in the years since it has become more and more clear that that the implementation of a market mechanism alone cannot necessarily guarantee long-run security of supply (Rodilla & Batlle, 2010). Faced with this reality, regulators (often in conjunction with system operators) will still have to closely monitor the performance of market mechanisms for capacity expansion to assess if electricity demand will be supplied in the long term under reasonable standards of efficiency and quality.

This new role of regulators/system operators is particularly evident in the New England context, where the independent system operator is responsible for evaluating future system capacity needs to guarantee a certain level of reliability. Specifically, this is done through an evaluation of the need for an Installed Capacity Requirement fulfilled through the Forward Capacity Market mechanism.

In particular, one challenge which requires further innovation in regulatory tools to assess electric power system reliability and adequacy in a market context is how to take into consideration the increasing participation by the demand side. An active electricity demand is well known to have many benefits, but only recently has the maturity of some markets (for instance, in Europe full retail business liberalization has been realized) as well as certain technology developments (such as advanced meters and active demand response appliances like energy boxes) allowed consideration and in some cases realization of a larger percentage of electricity loads engaged in electricity markets. Though still small in most electricity markets relative to the size of electricity systems, the fraction of demand actively participating in markets will become more and more significant. In particular, referring for example again to the New England market case, around which this work is focused, some of the most active participants in the FCM auctions have been demand side agents.

The inevitable increase of active demand participation in short- and long-term markets will require regulators to rethink some fundamental principles of system operations and planning. In this thesis, we elaborate on one of the areas which will require attention as the elastic portion of the electricity demand curve becomes more prominent: the meaning and measurement of reliability.

In the context of current regulatory activities in the U.S., FERC order 745 suggests that demand response resources should be compensated for energy reductions at a rate equal to the wholesale market price (LMP) in all hours (FERC, 2011). This is a controversial proposal which has stimulated fierce debate, and the final decision on whether this will become a rule is expected soon. While this thesis does not deal specifically with the issue of the proper level of compensation for demand response resources in short term markets, the reliability definitions and metrics which we challenge are part of the same broader problem of reconciling demand participation in electricity markets with the legacy of central planning and operation.

Scope and Organization

This thesis takes as a starting point the framework proposed in Rodilla & Batlle (2011) and later expanded for the Spanish electric power market in Ayala (2011), in which a novel methodology is proposed to include demand elasticity in a Probabilistic Production Costing (PPC) model and on this basis, a regulatory discussion is raised on the significance of the traditional reliability measures.

Here we will apply the concept to a U.S. power system, the New England region of the Eastern Interconnection. This is an interesting case which first requires taking into consideration the active role played by the Independent System Operator in the assessment of system adequacy as manager of the Forward Capacity Market, as well as various methods of demand participation. Demand side participation in the New England context refers not just to demand response programs, but also to demand side bids in day-ahead markets; in the EU retail service has been fully liberalized, but this is not the case in New England.

In the U.S., this discussion is timely. Since FERC approved Order No. 745, system planners will necessarily have to redesign their modeling tools as well as reliability metrics to consider the contribution of demand response.

The consideration of demand response in PPC models is a problem that had not yet been properly solved until very recently, as Rodilla & Batlle (2011) show in their paper. PPC tools have been and are still being used by a good number of regulators to perform reliability

.assessments. For example, the regulator in Panama applies a PPC framework in order to assess the proper firm capacity (capacity credit) to be awarded to each generating unit in the system in the context of the capacity payment in force. In other cases, such as ISO-NE, regulators and ISOs resort to similar approaches to evaluate the future capacity needs to guarantee a certain level of system reliability.

The point Rodilla & Batlle (2010) raise after introducing the PPC model evolution is that in a context of growing demand side participation in wholesale markets, considering the contribution of demand response to the system reliability in the long run is a key issue. As such, one of the objectives of this thesis is to try to quantify for a real-size case how when this is done, the traditional reliability metrics commonly used in these assessments have to be redefined.

The organization of this document is as follows:

Section 2 presents background information on power systems reliability and demand response. This information is necessary in order to understand the relevant aspects of New England's power system.

Section 3 describes computations used to estimate reliability. This includes

- A modified Probabilistic Production Costing model to estimate the loss of load probability and other traditional metrics, as well as the value of non-purchased energy considering demand elasticity.
- A Neural Gas clustering algorithm used to address the time-varying nature of electricity market data. This algorithm is used to help generate representative supply and demand curves which are taken as inputs to the Probabilistic Production Costing model.

Section 4 applies these calculations to New England's power system, accounting for the different characteristics of that system compared to the Spanish system modeled in Ayala (2011).

Section 5 makes brief conclusions based on the work of this thesis, and Section 6 contains references cited.

2 Background

In order to understand the study of New England's power system described in Section 4 and the models used in that study described in Section 3, it is first necessary to cover two foundational concepts: reliability and the changing role of demand in power systems.

2.1 Reliability of Power Systems

In general, reliability of power systems refers to their ability to generate and deliver electrical energy to customers without failure. Power systems are complex, however, and there are many tasks which are required to achieve the goal of a reliable system. Due to this complexity, it is useful to classify several dimensions of reliability, and to develop metrics and benchmarks to measure success along each dimension. In this section, we will define the several dimensions of power systems reliability and then delve further into the particular two dimensions of interest in this thesis: adequacy and firmness. We will discuss the benchmark commonly used by planners to define an adequate power system, the loss of load probability (LOLP), and two criticisms of that benchmark.

2.1.1 Dimensions of Reliability

The North American Electric Reliability Corporation (NERC) defines two dimensions of bulk power system[2] reliability:

- *Adequacy* is "the ability of the electric system to supply the aggregate electric power and energy requirements of the electricity consumers at all times, taking into account scheduled and reasonably expected unscheduled outages of system components."
- *Operating Reliability* is "the ability of the electricity system to withstand sudden disturbances such as electric short circuits or unanticipated loss of system components." (NERC, 2010)

In other words, adequacy relates to the long-term issue of ensuring adequate generation resources and transmission capacity to meet load requirements, while operating reliability relates to short term issues which must be dealt with by system operators. The dimension of reliability which NERC refers to in the 2010 Long Term Reliability Assessment as operating reliability is also often referred to as *security.* Adequacy is maintained by appropriately planning for the addition of new generation and transmission facilities, while operating reliability is maintained by keeping adequate generation reserves ready for contingencies.

A growing number of authors in the literature recognize another dimension of reliability:

- *Firmness* is a short to medium term dimension of reliability defined as the ability of existing bulk power system facilities to efficiently supply electricity. Maintaining firmness mainly entails proper management of existing generation facilities, including purchasing fuel for thermal plants, water resource management for hydro, and coordinating maintenance scheduling (Batlle & Pérez-Arriaga, 2008).

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[2] The bulk power system refers collectively to generation and transmission facilities. The voltage level above which lines are considered 'transmission' rather than 'distribution' is different everywhere, but generally around 100 kV or 200 kV. Reliability of the bulk power system in the U.S. is the responsibility of NERC.

Of these three dimensions of reliability, adequacy and firmness are the ones of concern in this thesis. Note that the NERC definition of adequacy includes an implicit assumption that electricity consumers have some preset level of consumption which must be met by the system's generating resources. The central observation we make in this thesis is that while this was a safe assumption before the introduction of wholesale electricity markets, an electricity demand side which actively participates in the market and adjusts output based on the price of electricity has no such preset level of consumption. Thus, to the extent that electricity demand curves are increasingly elastic, this definition of adequacy fails to capture key information about the adequacy and firmness of the power system.

For the sake of simplicity, we will hereafter refer to reliability as defined above, although in the market setting reliability is a broader concept than these traditional definitions can account for.

2.1.2 Measures of System Adequacy

One common metric for system reliability is the Loss of Load Expectation (LOLE). Billinton & Allan (1996) define LOLE as the number of time units (hours or days) in a given period of study (months or years) during which generating capacity can be expected to fall short of demand. It is calculated by comparing projected load with the likelihood of generation capacity outages. This probabilistic measure is most often given in units of days per year or hours per year depending on the type of load data used in formulating the index; for example, if an hourly load duration curve for one year is used, then the result will be in units of hours per year.

Loss of Load Probability (LOLP) is a similar metric, defined as the probability that load will exceed available generation capacity in a given period of study. Unlike LOLE, this metric is unitless and gives a simple probability of load exceeding generation in a given period of study.

Definitions of LOLE and LOLP are not consistent among all sources. For example, Energy and Environmental Economics (2004) defines LOLP specifically as "the expected number of days in the year when the daily peak demand exceeds the available generating capacity" and LOLE as hourly loss of load expectation, similar to LOLP but with hourly demands used in the calculation. Though some ambiguity exists in these terms, in this thesis we will use the definitions presented in the first two paragraphs of this section.

The ubiquitous reliability benchmark of "one day in ten years" is a Loss of Load Expectation, but LOLE is not typically calculated for a time period of 10 years. In practice, this standard is often translated to a similar LOLE of 0.1 days per year or 2.4 hours per year. See, for example, ISO-NE (2011e). A LOLE of 2.4 hours per year means that in a given year load is expected to exceed available generation for an average of 2.4 hours; a true LOLE of 1 day in 10 years would mean that over a period of 10 years load is expected to exceed available generation for an average of one day out of 3650.

In addition to the LOLE, other metrics are used in an attempt to characterize the severity, frequency, or duration of outages. One other commonly used metric is the Expected Non-Served Energy, (ENSE), also known as expected energy not supplied (EENS) or Expected Unserved Energy (EUE). This is given as a quantity of demanded energy which is not expected to be met by generation over a given time period. The information provided by ENSE is an important supplement to LOLE ; a LOLE of one day per year for a given system would have very different implications if the EENS was 1% of the load for that day or 50%. Like LOLE and LOLP, unserved energy metric definitions are not globally standardized. To understand the principles behind reliability indices and metrics, reference (Billinton & Allan, 1996) is the definitive work.

2.1.3 Shortcomings of One Day in Ten Years

As mentioned, 'one day in ten years' is commonly accepted as the benchmark for system planners. However, it has been demonstrated that this widespread benchmark for system planners is not optimal and in fact results in a system which is too reliable – that is, a system where electricity customers would prefer to pay lower rates in exchange for some reduction in reliability.

Telson (1975) calculated that the common reliability goal of 1 day in 10 years might be more costly than consumers are inclined to pay for, and that a more appropriate goal might be 5 days in 10 years. He also noted that the 1 day in 10 years criterion was first used simply "because it seemed to lead to good results" and that it was widely adopted following intense public pressure for high reliability following the Northeast blackout of 1965. Though it was widely adopted at that time, no one seemed to know why the measure was used. Even in 1972, the 1 day in 10 years criterion was already considered by some to be an "old myth" (Telson, 1972).

Other authors have agreed with Telson that there are shortcomings of the one day in ten years criteron, for example Chao (1983) and Wilson (2010). Because the methodology used in Wilson (2010) is straightforward, it is presented briefly in Figure 2 to illustrate why the LOLE planning criterion of 1 day in 10 years is too stringent.

Wilson begins with the law of economics which states that efficiency is achieved in a market when marginal benefits are equal to marginal costs. In this case, the marginal cost is the capacity cost of generation measured in $/MW. This value is relatively easy to determine based on the cost of installing and maintaining new generators. Marginal benefits are the reliability benefits experienced by customers as a result of capacity costs incurred. These are more difficult to measure, but can be calculated by the product of the value of lost load to customers in $/MWh, the average duration of an electricity outage, and the expected number of outages per year. Depending on the definitions used, this last quantity can be interpreted as the LOLE. As shown in Figure 2, optimal LOLE can be calculated by estimating value of lost load and the average outage time.

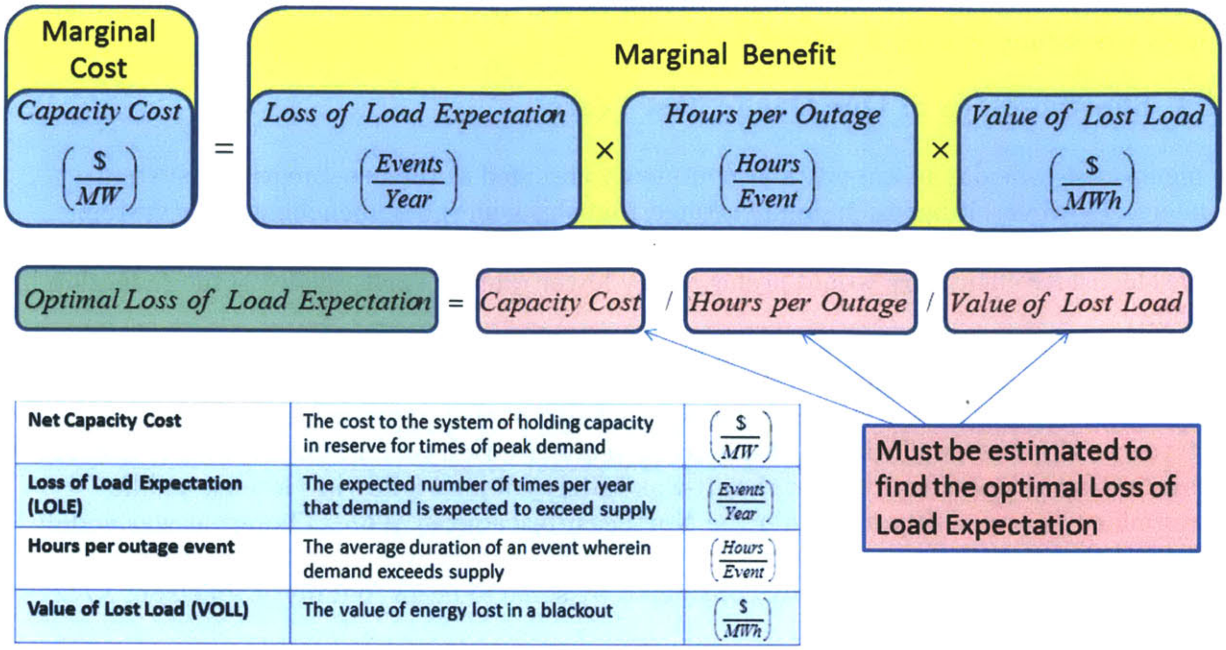

Figure 2: Wilson's approach to estimating optimal LOLE

Table 1 shows the results of Wilson's calculations using a range of reasonable estimates of the Value of Lost Load and capacity cost. The results indicate that the ubiquitous one day in ten years criterion could be too stringent by up to one or two orders of magnitude.

Value of Lost Load ($/MWh)	Net Capacity Cost ($/MW-year)	Hours per Outage Event (Hours/Event)	Optimal LOLE (Events/Year)
2,000	120,000	5	12.0
2,000	80,000	5	8.0
2,000	40,000	5	4.0
4,000	120,000	5	6.0
4,000	80,000	5	4.0
4,000	40,000	5	2.0
20,000	120,000	5	1.2
20,000	80,000	5	0.8
20,000	40,000	5	0.4

Table 1: Results of Wilson's estimate of optimal LOLE for various assumed values of lost load and capacity costs

In addition to this indication that the one day in ten years LOLE is too stringent, Wilson also points out that system planners often make conservative assumptions resulting in systems having LOLEs which are in reality even more reliable than one day in ten years. He notes that in in the past, the consequences of overbuilding generation were minimized by consistently high levels of demand growth which eventually erased any overcapacity. However, the fast growth in electricity demand which characterized early years of the one day in ten years criterion have come to an end. Today, U.S. demand growth is slower and more volatile.

2.1.4 Conclusion

Reliability is commonly measured with a metric known as the Loss of Load Expectation (LOLE) or Loss of Load Probability (LOLP). A standard of reliability generally used by system planners is that the generation resources of a system be inadequate to meet demand no more than once every ten years. This translates to a LOLE of no more than 0.1 days per year. Past work has shown that this standard of reliability is likely too stringent, and that customers would in fact prefer a discounted electricity rate along with a lower level of reliability over current electricity rates and reliability levels.

In the section defining dimensions of reliability, we noted that the NERC definition of adequacy takes as a given that there is some set level of electricity demand which must be met by generators through appropriate system planning. Notice now that this implicit assumption is reflected in the metrics for measuring adequacy. LOLE and LOLP as well as EENS each assume that generation must be sufficient to meet this predefined level of demand. In the next section, we introduce the reason that this implicit assumption of adequacy metrics is becoming less acceptable: increasingly responsive electricity demand. Information provided by demand bids allows us to consider not just the frequency of scarcity events, but also the actual costs of them.

2.2 Responsive Electricity Demand

The Federal Energy Regulatory Commission defines demand response as:

"Changes in electric use by demand-side resources from their normal consumption patterns in response to changes in the price of electricity, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized." (FERC, 2009)

In simpler terms, demand response is electricity demand which adjusts to price signals or other system conditions.

2.2.1 Benefits of Responsive Demand

Demand for electrical power varies throughout the day and with the seasons. During extreme weather conditions, demand is high as customers run air conditioners or heaters. A typical three days of demand is shown for ISO New England in Figure 3. Demand is highest in the evenings as people get home from work, turn on electrical devices, and use hot water. Demand is lowest in the middle of the night while people sleep.

Cost of electricity is linked not only to the quantity of energy produced, but also to the capacity to produce power. The quantity of energy required by the demand shown in Figure 3 is the area beneath the curve. The capacity required to produce that energy, however, is represented by the maximum point on that curve. A smoother demand curve will result in lower system costs, even if the total quantity of energy is the same.

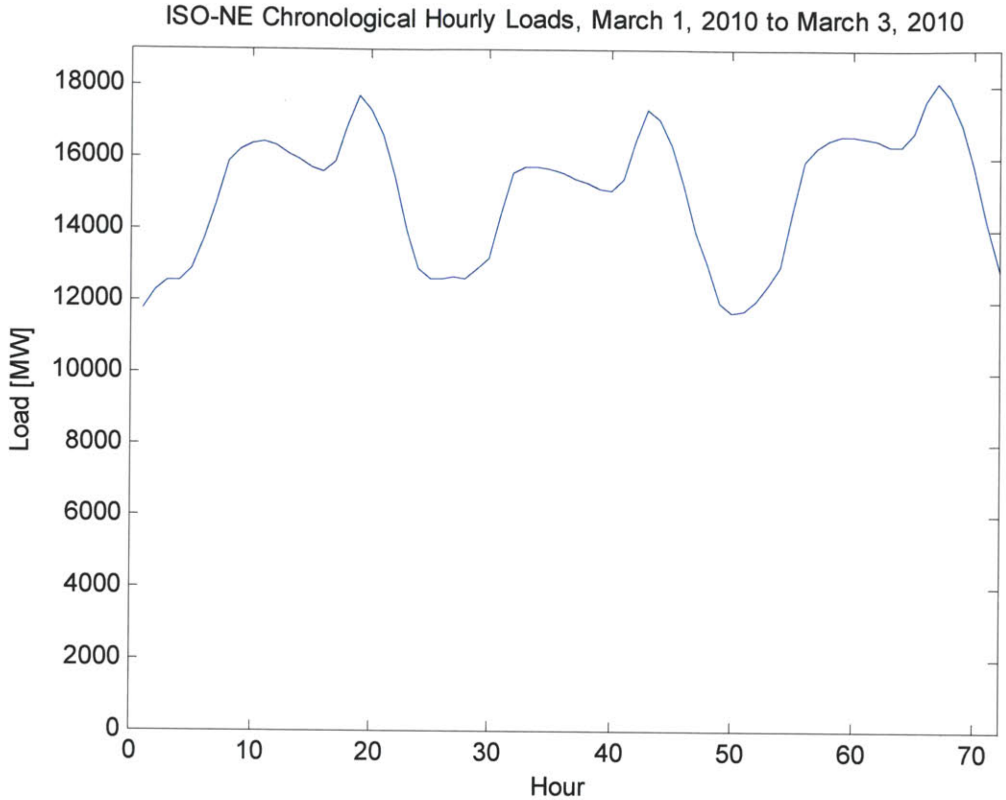

Figure 3: Demand in ISO-NE for three days from March 1-3 2010

Since the vast majority of retail customers have until very recently been (and most cases still are) charged the same price for electricity at all times during the day, they have no incentive to help keep system costs low by shifting use from times of peak demand to times of low demand. Thus, the first benefit which would be introduced by price responsive demand is reduction in system costs due to load shifting from peaks to valleys.

This benefit could be significant. It has been estimated that nationwide, a peak load reduction of 5% annually could result in a discounted present value of $35 billion[3] over 20 years (Faruqui, Hledik, Newell, & Pfeifenberger, 2007). However, there is significant uncertainty in this estimate; the study also reports a 90% probability of $18 billion in avoided cost and a 10% probability of $61 billion. The reason for the potential for such large benefits can be conceptualized by viewing a load duration curve, as in Figure 4. It can be seen that peak demand is reached only during a very small portion of the hours in a year, represented by the left-most portion of the line. If some demand from these few peak hours can be shifted to other hours, it will allow significant reduction in the cost of holding capacity in reserve for those few hours.

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[3] 2007$

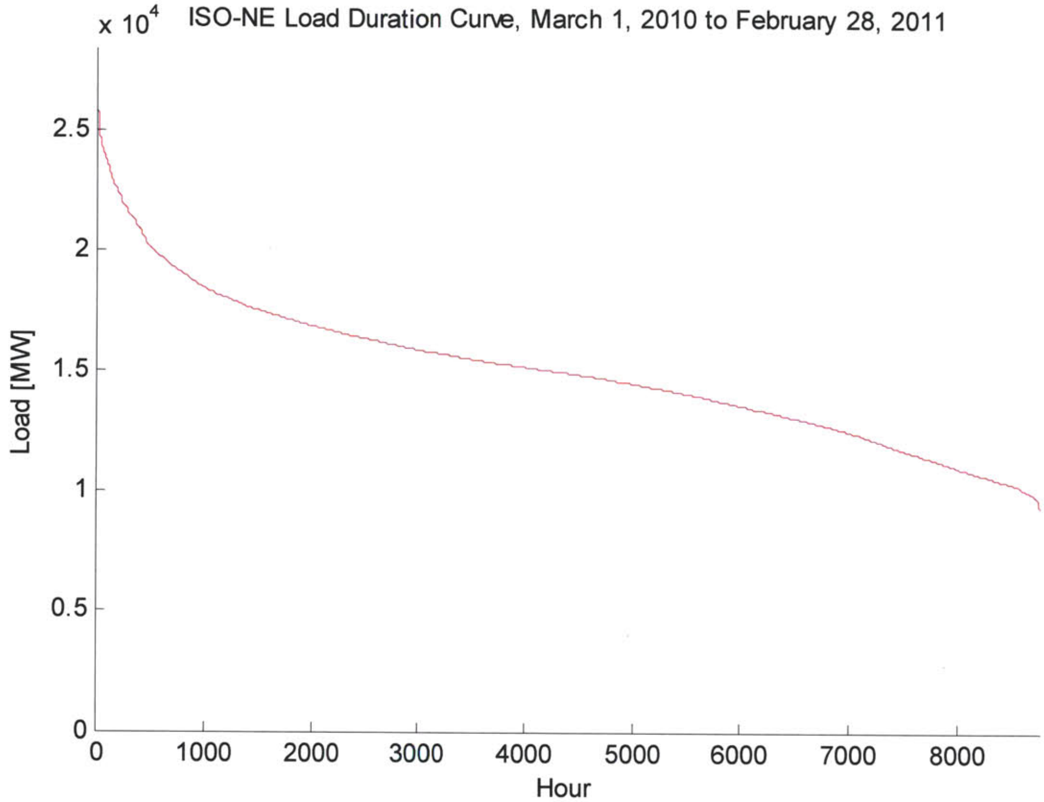

Figure 4: Load duration curve, ISO-NE March 2010 – February 2011

In addition to shifting consumption from peaks to valleys, it is also possible (though not given) that price-responsive demand could result in an overall reduction in the quantity of energy consumed; in other words, that programs allowing demand to respond to price signals might incent electricity users to conserve energy or to invest in more energy efficient equipment, in addition to shifting energy use from capacity peaks to valleys. The benefits of energy efficiency and conservation are important topics which have been covered extensively elsewhere; see for example Sutherland (1991).

Improved reliability is another benefit of price-responsive demand. It is not uncommon for a problem to occur with a generator, resulting in a sudden loss of power production capacity in a system. Such an event sets off a particular reaction in a system with a flat-rate tariff. First, system operators must bring other generators online quickly to fill the gap left by the offline generator. Generators capable of coming online very quickly are also more expensive than other generators, so system cost goes up. Additionally, during this time the system is in a reduced security state – further problems could result in loss of load.

Demand response or other price-based incentives help reduce this risk of blackouts, since system operators no longer battle to correct the system by themselves. Rather, they have the help of customers, who know through a price-based or other signal that a problem exists and reduce their usage accordingly.

Another potential benefit of demand response is a reduction in greenhouse gas emissions. Reducing the total quantity of energy consumed through energy efficiency or conservation certainly has this effect. Shifting consumption from peak periods to low periods as described above could also reduce greenhouse gas emissions. Usually, load at extreme peaks is served by inefficient, high emissions generating units because such facilities are capable of starting up and ramping quickly, and because sunk costs in these facilities make investment in other peaking plants irrational from a cost perspective. Reducing peak-load demand would reduce the use of such peaking plants and shift it to base load. In areas where base load is clean – the Pacific Northwest and its hydroelectric power, for example – this would reduce emissions. However, where base load is also dirty, such as the Midwest and its coal generation, shifting from peaking plants to base load plants would not necessarily reduce emissions.

The complexity of power systems makes the benefits described above anything but transparent. Determining the magnitude of benefits under certain specific modeling assumptions may be possible, but for the average electricity customer great uncertainty exists. Furthermore, surveys suggest that a large portion of the public does not believe that reducing greenhouse gas emissions is beneficial; other customers might believe that reducing greenhouse gas emissions is the most important benefit of all. Despite these uncertainties, system operators and governments have indicated that demand response will be a growing resource in tomorrow's electricity markets.

Implementations of Demand Response

From a theoretical standpoint, the best way to implement time-varying pricing at the retail level is to simply create retail tariffs which change in real-time (Borenstein & Holland, 2005), to track the changing prices in wholesale electricity markets. This would pass ideal price incentives along to consumers, reflecting the marginal system cost at all times; economically speaking, nothing would be better than universal real-time prices. However, in practice there are significant barriers associated with implementing such an approach. The most significant of these is a lack of maturity and reluctance on the part of demand.

In addition, other barriers include the cost of metering equipment necessary to convey price information and report usage for each consumer in real time, and a potential loss of privacy. Real-time energy use data has the potential to reveal private information about one's activities around the home. With such data it is easy to tell if an individual is at home or away, and it may even be possible to tell what activities the individual engaged in at any given time during the day – whether it is washing clothes, making toast, or taking a shower. Though such detailed data could be the source of both beneficial and harmful action, it is the latter which customers seem to focus on.

For these reasons, a universal real-time price program is not likely in the near future, although the widespread roll-out of advanced meters is bringing it a step closer to reality. In the absence of a full real-time price signal, other options exist. Time-of-use pricing, wherein the price depends only on the time of day, and critical peak pricing, wherein price is increased only infrequently based on forecasted high prices and announced to customers beforehand, are attractive because the metering equipment required is not as sophisticated as that needed for real-time pricing.

The demand participation option which tends to receive the most attention is demand response (DR), which in general sets forth methods for customers to be compensated for reducing their usage below the baseline which they would normally consume. Typically, demand response programs are implemented as part of wholesale electricity markets, with customers or an agent acting on behalf of a group of customers bidding into the wholesale market with the price and quantity of load they would be willing to curtail at a given time. In the case example presented later in this thesis, the various types of DR programs in New England as well as other methods of demand participation will be enumerated, explained, and modeled.

2.3 Conclusion: A Need for New Metrics

In this section, we have introduced power systems reliability and metrics used to measure resource adequacy: LOLE/LOLP and EENS. We have shown that the commonly used adequacy planning criterion, LOLE of 'one day in ten years', is flawed and that this benchmark does not reflect the true preferences of electricity customers. These metrics are based on the assumption that the cost of non-served energy beyond the threshold administratively defined by the regulator outweighs any demand side opportunity cost. Furthermore we have pointed out that each of the adequacy metrics carries the implicit assumption of fixed electricity demand. Finally, we have enumerated the benefits of responsive electricity demand. The fact that electricity demand is likely to become increasingly responsive in the future motivates the need for new metrics to supplement LOLE, metrics which are capable of capturing the characteristics of responsive demand.

In the next section, we introduce one of the approaches that have traditionally been used to calculate reliability metrics, the Probabilistic Production Costing model. We will describe a recent evolution of this approach that allows proper representation of demand responsiveness and apply the methodology to the of New England power system. In particular, we also introduce the clustering algorithm used to deal with the time-varying nature of the markets, and explain how the algorithm will be used to help generate appropriate representative demand and supply curves for use in the Probabilistic Production Costing model.

3 Description of Modeling[4]

In the previous section, we introduced the concepts of reliability of electricity supply and demand response. In this section, we turn to the Probabilistic Production Costing (PPC) model which has often been used by regulators to calculate these metrics (among other uses). We explain the details of this model, and introduce a recent innovation to the classical PPC model which accounts for responsive demand.

We also explain the Neural Gas clustering algorithm which is used to help determine appropriate representative supply and demand curves observed in the market. Generating representative curves is necessary because we use the PPC not to model every hour of power system dispatch but rather to consider several time blocks sharing common characteristics.

3.1 Estimating Reliability with a Probabilistic Production Costing Model

Probabilistic Production Costing (PPC) models been used for many years as a tool for decision support in power systems (Rodilla, 2010). PPC models are especially useful as a tool for centralized system planners performing long-term analysis for system expansion. PPC models allow planners to carry out reliability assessments of practically sized power systems with relatively little computational power. This is achieved by focusing on the random nature of the few, most relevant variables in long-term planning: quantity of demand and capacity of each generating unit. However, performing long-term analysis in this way necessitates severe simplifications in terms of the short- and medium-term constraints of the system.

Scholars have actively researched various forms of the PPC model since the late 1960s, when the advantages of low computational requirements were especially important. The most basic model pertains to a system composed only of thermal generators (Booth, 1972).

The main results of the basic PPC model are reliability measures, expected production schedules, and expected production costs. Reliability measure outputs of the PPC model may include (see Section 2.1.2):

- Loss of Load Probability (LOLP)
- Loss of Load Expectation (LOLE)
- Expected Non-Served Energy (ENSE).

A generating unit's expected production schedule is the quantity of energy that unit is expected to produce over the time period of study. Expected production cost is the expected cost of producing that amount of energy.

Over the years, there have been numerous variations on and additions to this conventional PPC model, allowing inclusion of various other characteristics of power systems. One important addition to the basic approach is to include hydroelectric generators within the PPC framework. Such models make assumptions about the energy-limited nature of hydro, and may also consider its unique time-dependent characteristics. A selection of important works in this area includes Finger (1979), Ramos & Arrojo (1991), Malik (2004), Conejo (1987), and Invernizzi, Mansoni, & Rivoiro (1988).

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[4] A significant part of this discussion benefits from Rodilla & Batlle (2011) and Ayala (2011)

Another line of development of PPC models aims to expand the usefulness of reliability results by revealing additional information about the frequency and duration of lost load, rather than simple probabilities and quantity of energy as found through LOLE and ENSE. An example of an additional result which might be calculated from such efforts is the mean time between situations of extreme resource scarcity. A variety of approaches to this end can be found in Ringlee & Wood (1969), Ayoub & Patton (1976), and Finger (1979).

Another application of PPC models helps regulators determine the marginal contribution of each generating unit to system reliability. An early work in this area is Garver (1966). More recently, concern has been especially apparent in the area of variable energy resources and Kahn addresses the contribution of wind energy to reliability in Kahn (2004). Such calculations are important in a market setting for tasks such as determining compensation for generators in systems where capacity payments are used.

3.1.1 The Conventional Thermal System Model

This section describes the basic thermal model which is the core of the model to be applied to the New England power system in the next section. The description of the thermal model includes underlying assumptions, convolution for dispatching generators, and a more thorough description of results than was given in the introduction.

Assumptions

The traditional PPC model is built upon simplifying assumptions about both generating units and demand. Generating units are assumed to be capable of producing at full capacity and at constant operating cost at all times, except periods where the unit is off line due to a forced outage. Demand is assumed to be both stochastic and inelastic.

The assumption about generating units is a major simplification. Many times, units have partial forced outages which prevent them from producing at full capacity but not from producing at some level between minimum and maximum capacity. The assumption is helpful because it allows generators to be modeled as random variables with only two states. In some cases, this assumption can lead to misleading results, especially in relatively small systems where the contribution of a single generator to total output is significant.

Stochastic demand refers to the treatment of demand as random across time periods which are not chronologically linked. For example, if the period of study of a PPC model is a year, one might choose to model the demand for each hour in the year. This demand is modeled as a random variable which treats the demand level in any given hour as completely random with the probability distribution approximated by the load duration curve of demand in each hour of the year. This will be defined more formally in the next section.

The assumption that demand is inelastic means that demand is fixed regardless of the cost of producing electricity (in a vertically integrated setting) or the wholesale market price (in a market setting). This assumption, as we have argued in earlier sections, was perfectly valid in the past but increasingly problematic as demand participation increases.

As we have said before, the basic PPC model checks for a simple reliability violation: an event wherein available generation is unable to meet expected demand. Computationally, this event is represented as the difference of the random variable representing demand and the random variables representing generation. This result is the LOLP when the model targets a generic random hour, and can also yield LOLE when this simplest form is extended from a random generic hour.

A further key assumption of this traditional PPC model is that the random variable representing demand and the random variables representing generation capacity of each unit are independent. This is a very important assumption because it allows us to perform a simple computation to calculate the difference of these variables: convolution. The convolution of the probability distribution functions of two random variables is equal to their sum (or difference).

In the following sections, we further explain the details of modeling demand and generation units, and go on to demonstrate how the convolution operation simulates dispatching generation units to meet demand. We also show the detailed results of this operation and how to interpret the output.

Inputs

The traditional PPC model for thermal generators takes as inputs a stochastic representation of demand and representations of all thermal generators in the system characterized by their probable output levels and merit order. This is now explained in detail.

Demand

Demand data can be presented in several ways. The simplest way is chronologically, with demand levels ordered in time from first to last. In this representation, the load levels can be seen to oscillate between high and low depending on the time of day, season, and temperature. Sometimes, it is more useful to display load levels in order from highest to lowest. This form of display is called the load duration curve (LDC), useful when we want to see how often load reaches very high levels or to divide up a long timeframe such as a year into several representative 'chunks' based on load level. Both of these presentations of load data for one year can be seen in Figure 5.

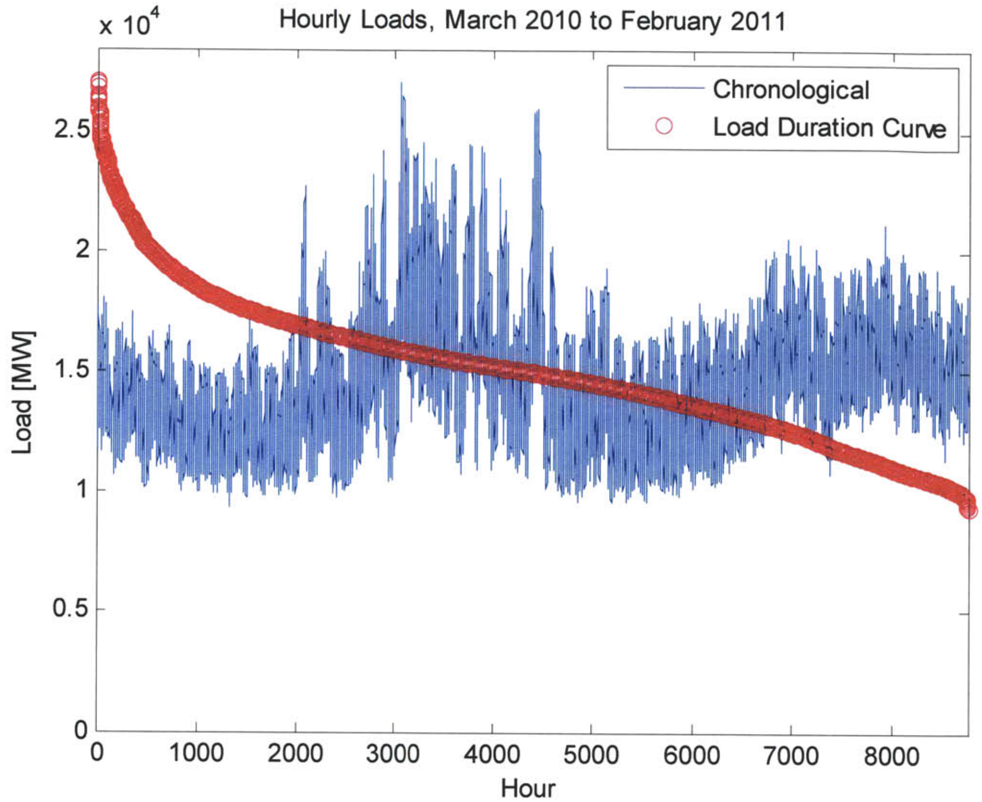

Figure 5: Chronological measured load data and the load duration curve

In order to model demand as a random variable, we must obtain its probability distribution. This probability distribution should represent the likelihood of all possible demand levels occurring in some generic random hour. Luckily, this distribution function is very easy to obtain from the LDC. We do this by calculating the load complementary distribution function (LCDF) as a proxy for the true theoretical probability distribution of load levels. The LCDF is also sometime called the inverse load duration curve (ILDC) or the de-cumulative distribution function (DDF)

Formally, the true distribution is defined over a set of k hourly load levels L as $S_k(L)$. An estimator for $S_k(L)$ obtained from historical observations is denoted as $\hat{S}_k(L)$. $\hat{S}_k(L)$ and the LCDF are one and the same, and both are easy to obtain from the LDC. The estimator converges to the true distribution function as k approaches infinity:

$$\lim_{k\to\infty} \hat{S}_k(L) = S_k(L)$$

In order to obtain $\hat{S}_k(L)$ from the hourly load data, we treat hourly peak loads as a set of independent and identically distributed random load levels, $(l_1, l_2 \dots l_k)$ with the common distribution $S(L)$. From these observations of hourly load $(l_1, l_2 \dots l_k)$, we define the LCDF as

$$\hat{S}_k(L) = \frac{(NumberOfObservations \geq L)}{TotalNumberOfObservations} = \frac{1}{k}\sum_{i=1}^{k}\{l_i \geq L\}$$

Intuitively, we will take some historical load data (a year's worth, for example) and create the LCDF by calculating the percentage of time during which the measured load was greater than or equal to each load level. The LDCF obtained from the data shown in Figure 5 can be seen in Figure 6.

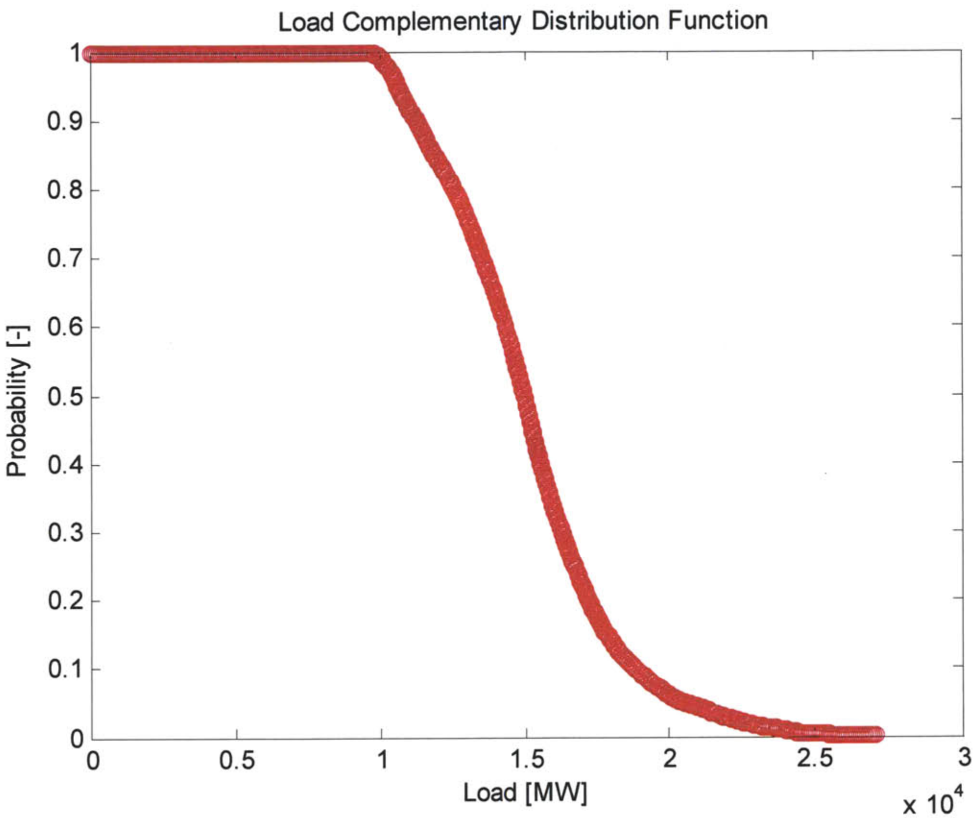

Figure 6: Example of a load complementary distribution function

In the transformation from LDC to LCDF, a subtle shift in the meaning of this data has taken place. While the LDC is demand data arranged as a monotonically decreasing function, the LCDF is a distribution function for the demand level in some random hour.

For further reading on probability concepts, see Shorack & Wellner (1986) and Van der Vaart (1998); for more on representations of demand, see Wood & Wollenberg (1996).

Thermal Generators

Two characteristics of thermal generators are considered in the PPC model, although the first one of them takes a significantly higher level of priority when applying the model to reliability assessments: 1) the probable output level of each generator and 2) the merit order of the generators; that is, the order of the generators when arranged from lowest variable cost to highest variable cost. If the costs themselves are not known, but the order is, then the PPC model can only calculate reliability metrics and schedules; if the variable costs are known or estimated, then the PPC model can also give information about the total cost of each generator's electricity production.

Each thermal generator in the system will be modeled as an independent discrete random variable with two possible values. These values correspond to the output of each generator at full capacity and zero capacity. In order to represent this mathematically, a random variable with a Bernoulli distribution is multiplied by the generator's maximum capacity.

A Bernoulli distribution is a discrete probability distribution with two possible values, 1 and 0. The probability that a Bernoulli random variable will take the value 1 is denoted as p, the probability of success. The probability that a Bernoulli random variable will take the value 0 is denoted as q, the probability of failure. Since only two outcomes are possible, 1 and 0, note that $q = 1 - p$.

In terms of our generator modeling, the probability of failure q is commonly known as the generator's forced outage rate (FOR). If we denote the available capacity of a thermal generator as Q and its maximum possible output as $\bar{q}$, then the probability mass function PMF m_Q of the available capacity Q is given as:

$$m_Q = \begin{cases} 1 - FOR & & Q = \bar{q} \\ FOR & when & Q = 0 \\ 0 & & Otherwise \end{cases}$$

The PMF of a thermal generator is represented visually in Figure 7. Remember that $q = FOR$ and $p = 1 - FOR$

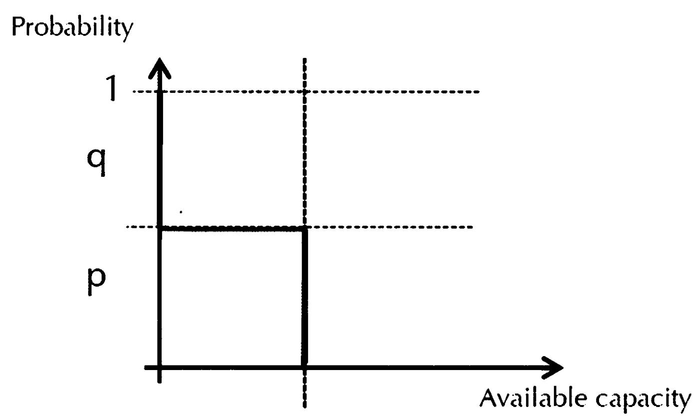

Figure 7: Probability mass function of a Bernoulli random variable, used to represent thermal generators in the PPC model

In addition to the probability mass function of each generator's output level, the other important characteristic of generators captured in the PPC model is their merit order. It is most convenient if the marginal cost of each generator is known; in this case the generating units can be ordered by increasing marginal costs to determine merit order, and more information can be calculated about generating costs. However, all that is required for the basic PPC model is knowledge of the order in which the units should be dispatched[5].

Convolution

Now that we have established the 'inputs' to the Probabilistic Production Costing model, 1) the load complementary distribution function and 2) the binary random variables representing each generator, we can show the computations necessary to obtain useful results. Though several pieces of information can be obtained from the PPC model, it is convenient as we describe the model to first attempt to find the system LOLP. Intuitively, the LOLP is what is left when each of the generator random variables is subtracted from the random variable representing load; it is the probability that load will at some moment be greater than total generation.

Since we are assuming that all of the random variables are statistically independent, computation of the difference of these variables is straightforward: it is the convolution of their probability distribution functions.

To explain the algorithm, it is conceptually helpful to think of 'dispatching' each of the generators in turn, according to their merit order, in order to meet load. Since generators and load are represented by probability distributions, we are left after each subtraction with a probability that those generators which have already been 'dispatched' will be capable of meeting system load.

More formally, we can denote the equivalent load after dispatching the first n generating units by EqL_n. This is a random variable representing the unserved load after dispatching the first n generators. After dispatching the first generator in merit order, the equivalent load will be the difference of two random variables, the total system load L and the available capacity of the first generating unit Q_1:

$$EqL_1 = L - Q_1$$

The probability mass function of EqL_1 (the equivalent load after dispatching the first generating unit) can be found as the convolution of the probability mass functions of the random variables L and Q_1:

$$m_{EqL_1}(EqL_1 = l) = \sum_k m_L(k) \cdot m_{Q_1}(l - k)$$

Similarly, the equivalent load after dispatching the first n generating units can be expressed as:

$$EqL_n = L - \sum_{t=1}^{n} Q_t = EqL_{n-1} - Q_n$$

Where t is an index representing the merit order of the generating units.

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[5] It should be noted that though we can think about these successive convolutions as 'dispatching' each of the thermal units, we are dealing with random variables and the concept is distinct from economic dispatch during system operations.

The probability mass function can again be computed as the convolution of random variables involved in the subtraction operation, EqL_{n-1} and Q_n:

$$m_{EqL_n}(EqL_n = l) = \sum_k m_{EqL_{n-1}}(k) \cdot m_{Q_n}(l-k)$$

When the above expression is applied recursively for each of N generating units, the result is a series of equivalent loads $(EqL_1 \dots EqL_N)$. The equivalent load before the first convolution is performed is equal to the system load, $EqL_0 = L$, and each successive equivalent load represents the load to be served by remaining generators. The last equivalent load EqL_N is the amount of load which is expected to be unserved after all generators have been dispatched. This random variable can be used to find the LOLP and the ENSE.

Not only is convolution a relatively easy computation, but the calculation becomes even easier when we consider that generators are modeled as binary discrete variables.

Returning to our notation of the previous section discussing demand, assume that $S(EqL_n)$ is the load complementary distribution function of the equivalent load after dispatching the first n generating units, and that the n^{th} unit has a forced outage rate FOR_n and maximum output $\bar{q}_n$. The distribution function of the equivalent load after dispatching the first n generators can be computed as:

$$S(EqL_n = l) = FOR_n \cdot S(EqL_{n-1} = l) + (1 - FOR_n) \cdot S(EqL_{n-1} = l + \bar{q}_n)$$

This is a long expression, but it can be broken up as the sum of two intuitively logical terms.

The first term is $FOR_n \cdot S(EqL_{n-1} = l)$ and corresponds to the possibility that the n^{th} generator will experience an outage. $S(EqL_{n-1} = l)$ is the distribution function of un-served load before loading the n^{th} thermal unit. It makes sense that this term is multiplied by FOR_n, the probability that the n^{th} generator experiences an outage. If this happens, then equivalent load will remain at the previous level and have the distribution function $S(EqL_{n-1} = l)$.

The second term is $(1 - FOR_n) \cdot S(EqL_{n-1} = l + \bar{q}_n)$ and corresponds to the other possibility, that the n^{th} generator will be available with maximum capacity $\bar{q}_n$. The probability that this might happen is $(1 - FOR_n)$ and the resulting unserved load would have the distribution function $S(EqL_{n-1} = l + \bar{q}_n)$.

PPC Convolution: a simple graphical example

A short graphical example should help illustrate the concepts presented above. Consider the equivalent load distribution in Figure 8. This represents the load distribution after dispatching the first $n - 1$ generating units.

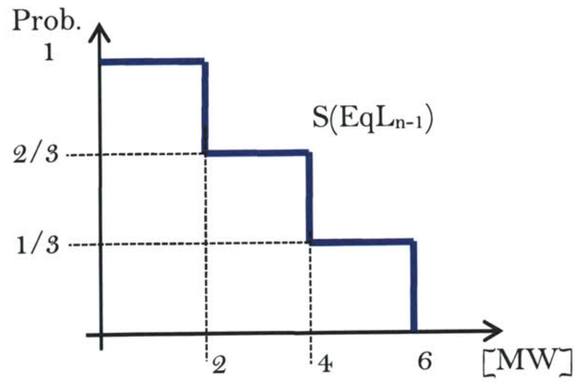

Figure 8: PPC illustrative example – equivalent load distribution function after dispatching n-1 generators (Ayala, 2011)

The capacity of the n^{th} generator is shown as the probability distribution function in Figure 9.

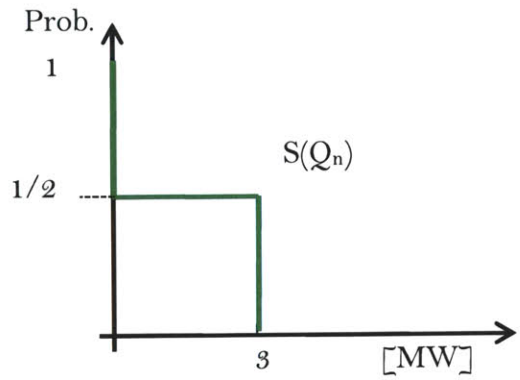

Figure 9: PPC illustrative example – distribution function of thermal unit available capacity (Ayala, 2011)

We will now illustrate how to find the equivalent load after dispatching the n^{th} generator shown in Figure 9. Referring to the practical convolution equation (the last equation of the section on convolution above) there are two possible scenarios. The n^{th} generator might be 1) available or 2) unavailable, and each of these has an associated probability, shown in Figure 9. The first scenario is represented in Figure 10. If the generator is unavailable, then the distribution function after dispatch is identical to the one before dispatching the generator.

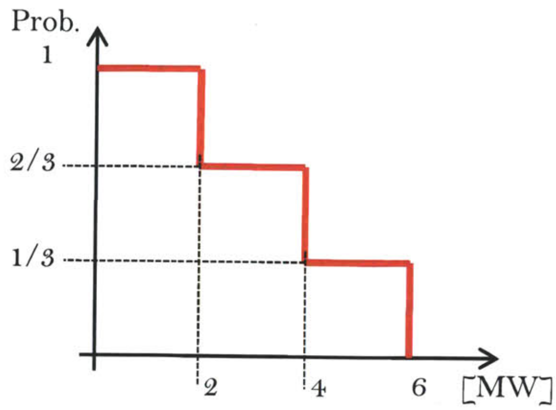

Figure 10: PPC illustrative example – distribution function of load in the case where the nth generator is not available (Ayala, 2011)

On the other hand, if the generator is available, then the generator will have the effect of reducing the equivalent load after dispatch. This is illustrated in Figure 11.

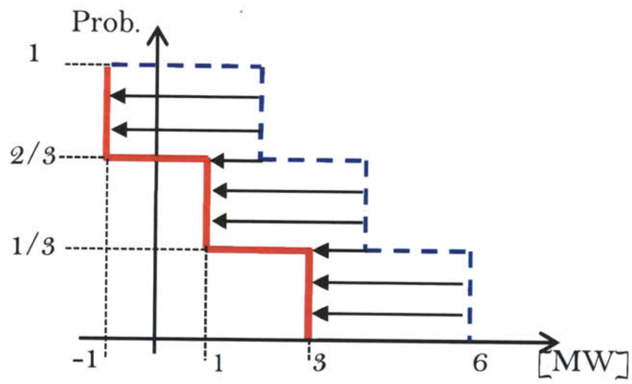

Figure 11: PPC illustrative example – distribution function of load in the case where the nth generator is available (Ayala, 2011)

Figure 12 illustrates the calculation from equation (3.1). Scenario 1 and Scenario 2 are weighted by FOR and $1 - FOR$, respectively. These two are then added to obtain the final equivalent load distribution function after dispatching the n^{th} unit.

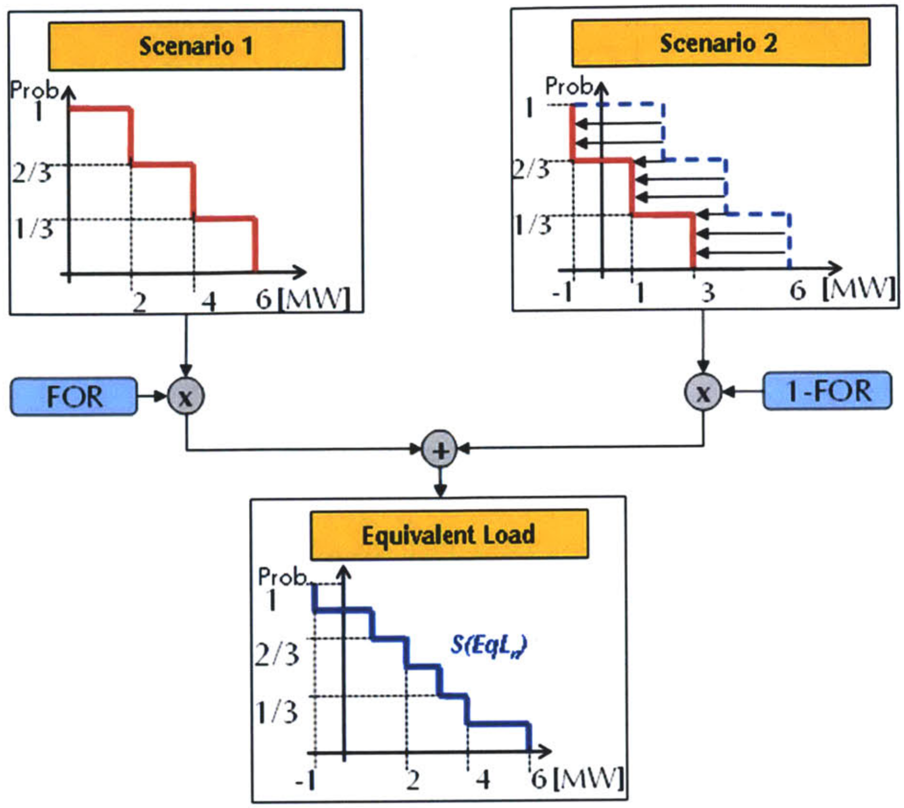

Figure 12: PPC illustrative example – convolution of discrete scenarios yields the equivalent load after the nth generator is dispatched (Ayala, 2011)

A more realistic example is shown in Figure 13. The dotted black curve on the far right represents the original load complementary distribution function, and moving left the successive blue lines are the equivalent loads after each generator is dispatched in merit order.

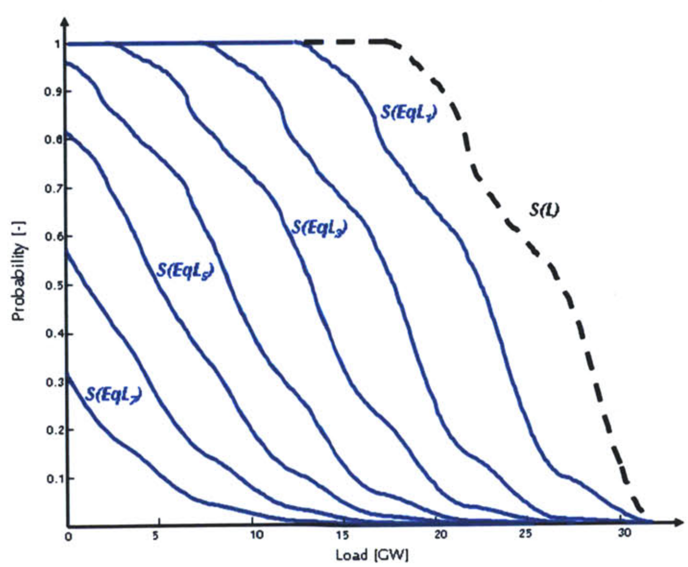

Figure 13: A realistic example of the PPC convolution results (Ayala, 2011)

In the next section, we discuss how to interpret the results of the convolutions and obtain useful reliability metrics and other information.

Results

Several important results from the PPC model are reliability measures, expected production schedules, and expected production costs. After dispatching all the N generators and finding all of the equivalent loads, there is a final equivalent load distribution function denoted in Figure 14 as the line under EqL_N. Graphically, two important results can be seen.

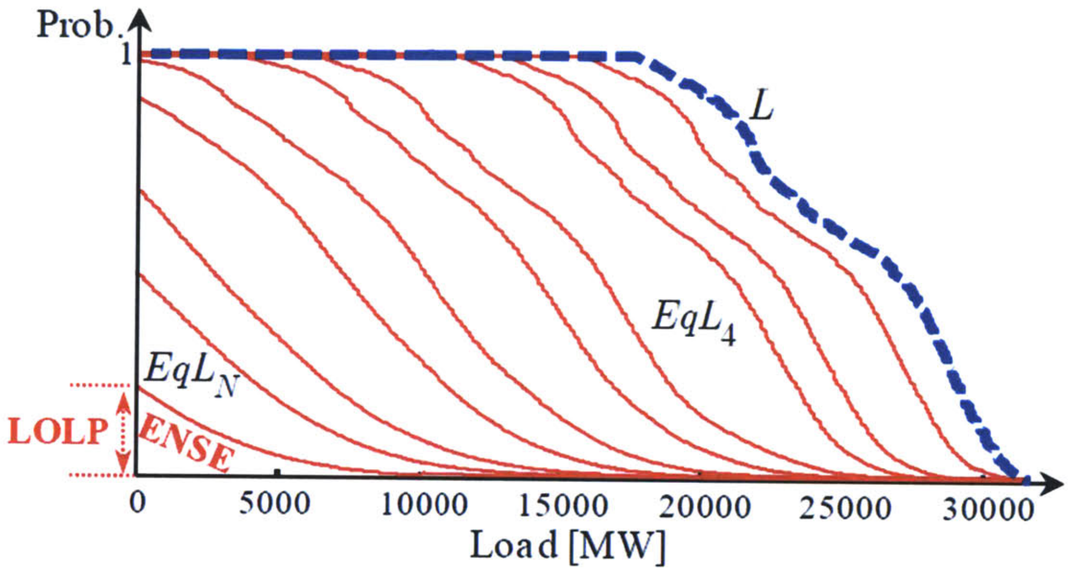

Figure 14: Results of the PPC model graphically (Rodilla, 2010)

First, the LOLP is the height where EqL_N intersects the vertical axis. Second, the ENSE is the area underneath this curve.

Important results of the PPC model are:

LOLP and LOLE

The LOLP is the probability that after all of the units are dispatched there will still be unmet demand. This is the point where the distribution function of non-served energy intersects the vertical axis:

$$LOLP = S(EqL_N = 0)$$

LOLE is similar to LOLP. We will define it more narrowly here as the number of hours within the study period that we expect insufficient generation, measured in units of hours. LOLP, on the other hand, is a unitless probability which tells us the likelihood that there will be an instance where generation is insufficient. Remember that we are studying a generic random hour within the period of study. To obtain the LOLE, just multiply the LOLP by the number of hours in the study period.

ENSE

Expected non-served energy is represented in Figure 14 as the area underneath the final equivalent load curve. It can be calculated as:

$$ENSE = \int_{l=0}^{l=+\infty} S\,(EqL_N = l) \cdot dl$$

Expected energy supplied and production cost of generating units

The expected energy supplied by the n^{th} unit can also be seen graphically. It is the area between the n^{th} curve and the $(n-1)^{th}$ curve. If E_n is the energy output of the n^{th} unit, then the expected energy output of the n^{th} unit is:

$$E[E_n] = \int_{l=0}^{l=+\infty} S\,(EqL_{n-1} = l) \cdot dl - \int_{l=0}^{l=+\infty} S\,(EqL_n = l) \cdot dl$$

The production cost may easily be calculated by multiplying the marginal cost of energy for that generating plant by the expected quantity of energy produced.

3.1.2 Introducing Demand Elasticity in the Model

Up until now, we have been discussing only the most basic form of the PPC model. As mentioned in the introduction to this section, there have been many innovations on this basic PPC model, each used to capture different elements missing from the basic model. We will not discuss most of these improvements in detail, instead skipping to a very recent innovation in the PPC model which allows the inclusion of price responsive demand in the model.

When we talk about demand response, there are two varieties. One, price sensitive demand, is demand which changes its behavior based on the price of electricity in wholesale electricity markets. Price-sensitive demand is the sort which was included.

Another sort of demand response is demand which reacts to actions on the part of the system operator when system reliability is jeopardized. These reliability related demand response programs are often triggered when operators see that operating reserves will fall below allowable levels. Thus, this sort of demand response can be thought of as reserve-sensitive demand; demand reductions are activated when reserves fall below some threshold.

Price-Sensitive Demand

The method used to include demand response in the PPC model is to treat demand bids as generators. In the traditional PPC model, demand was considered fixed in a given hour regardless of price. In other words, we had an inelastic demand curve for every hour. The demand curve shown in Figure 15, however, does include some elastic demand. In a traditional PPC model, the elastic nature of that demand would not be captured.

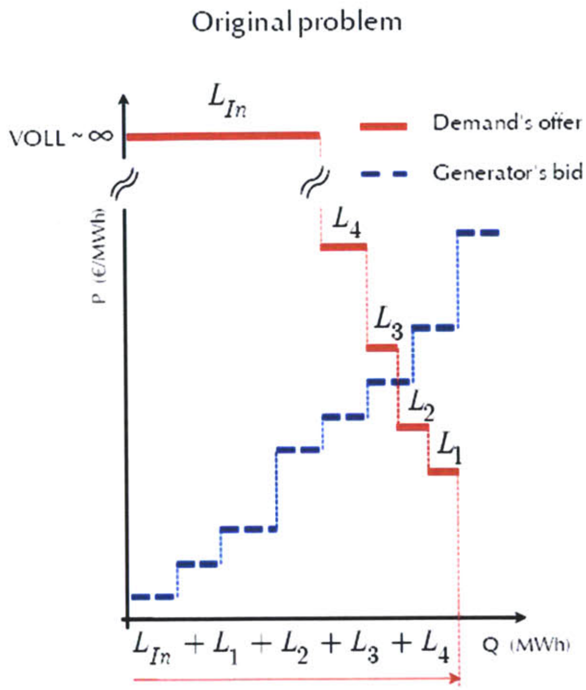

Figure 15: Normal supply and demand curves (Rodilla & Batlle, 2011)

Rodilla & Batlle (2011) propose that instead of ignoring the demand elasticity, we can treat each demand bid as a fictitious generators, translating the original PPC problem into an equivalent problem with fully inelastic demand and some supply bids which are in fact demand bids. The change from the original problem to the equivalent problem is shown in Figure 16.

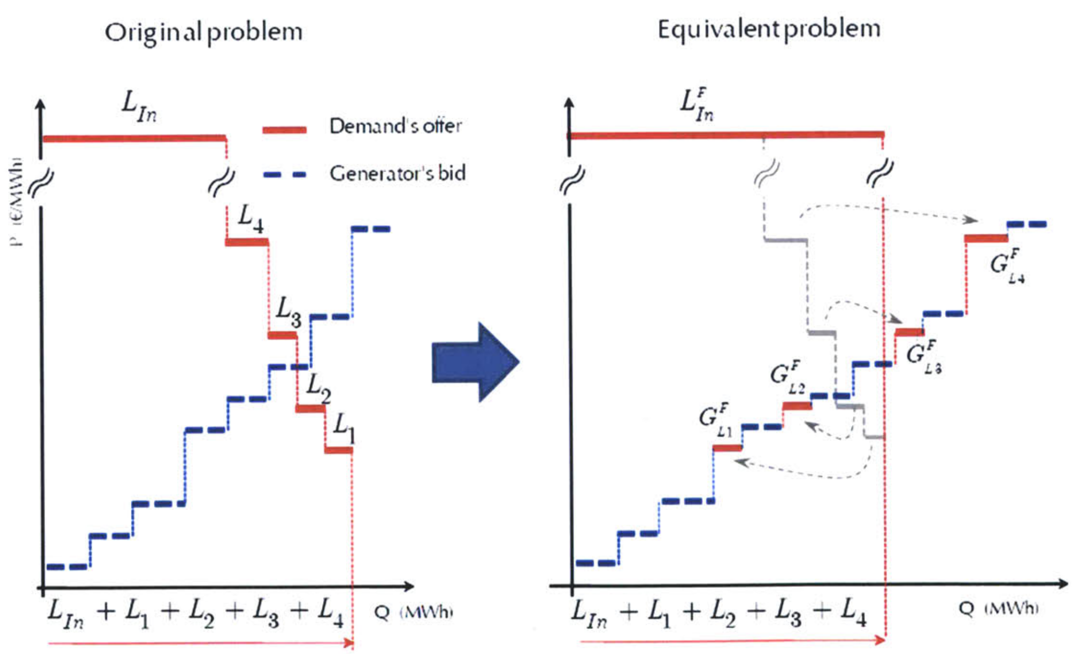

Figure 16: Demand bids as fictitious generators for PPC model (Rodilla & Batlle, 2011)

In their work, the authors show that the market outcome remains unchanged in the equivalent problem: generators committed are the same, as well as the demand which clears the market.

The parameters of the fictitious generator representing price-sensitive demand are:

$\bar{q}_f^{\psi}$: Maximum capacity of fictitious plant f in period ψ; equivalently, the demand bid quantity

MC_f^{ψ}: Marginal cost of fictitious generator f in period ψ; equivalently, the demand bid price

FOR_f^{ψ}: Forced outage rate of the fictitious generator f in period ψ

It would be possible also to assign a forced outage rate to these fictitious generators, representing a probability that the demand reduction is not available. However, to date this has not been implemented and so far fictitious generators have always been modeled with full availability ($FOR = 0$).

Reserve-Sensitive Demand

When system operators have the option of demand reductions as a tool to avert resource shortages, this should also be reflected in the reliability metrics such as LOLE and ENSE. In order to model these parameters in the PPC model, this interruptible load can be placed in the supply function merit order not according to bid price (since there is none) but according to some reserve margin.

The parameters characterizing the interruptible demand fictitious generators in the PPC model are:

$\bar{q}_{IL}^{\psi}$: Maximum capacity of fictitious plant f in period ψ; equivalently, the demand bid quantity

MC_{IL}^{ψ}: Marginal cost of fictitious generator f in period ψ; equivalently, the demand bid price

FOR_{IL}^{ψ}: Forced outage rate of the fictitious generator f in period ψ

The reserve margin $RM^{\psi}$is a quantity of power given as a percentage ε_{RM} of the maximum load in that period. These concepts are illustrated in Figure 17.

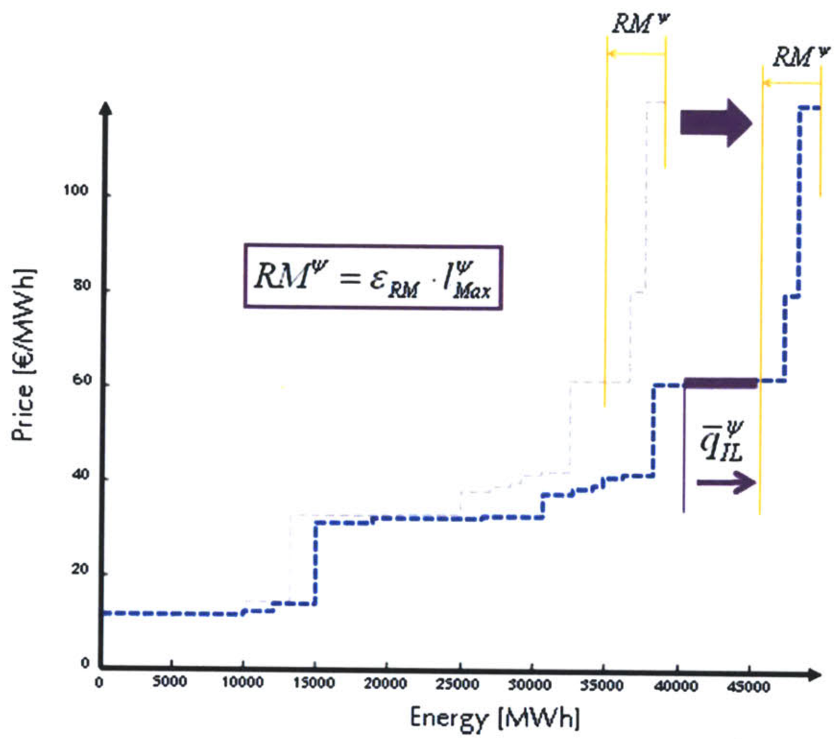

Figure 17: Graphical representation of reserve-sensitive demand in PPC supply curve (Ayala, 2011)

Measuring the Value of Non-Purchased Energy

The Concept of VNPE

When demand elasticity is significant, LOLP and ENSE cannot appropriately measure system reliability. In a market with fully elastic demand, the ENSE would always be equal to zero yet despite this 'perfect' reliability score, there could still be scarcity leading to inefficiency. In response to this observation, a new metric for the evaluation of market performance was proposed to supplement the traditional reliability metrics of LOLP and ENSE: the distribution function of the value of non-purchased energy.

Put succinctly, the value of non-purchased energy is the value of the energy which was bid upon but did not clear the market. Graphically, it is the area under the elastic portion of the demand curve. Given the marginal utility function for demand (the demand curve) and the marginal cost curve for supply (the supply curve), the value of non-purchased energy can be calculated as the quantity of energy which did not clear the market multiplied by the bid price of that energy. The concept is shown in Figure 18.

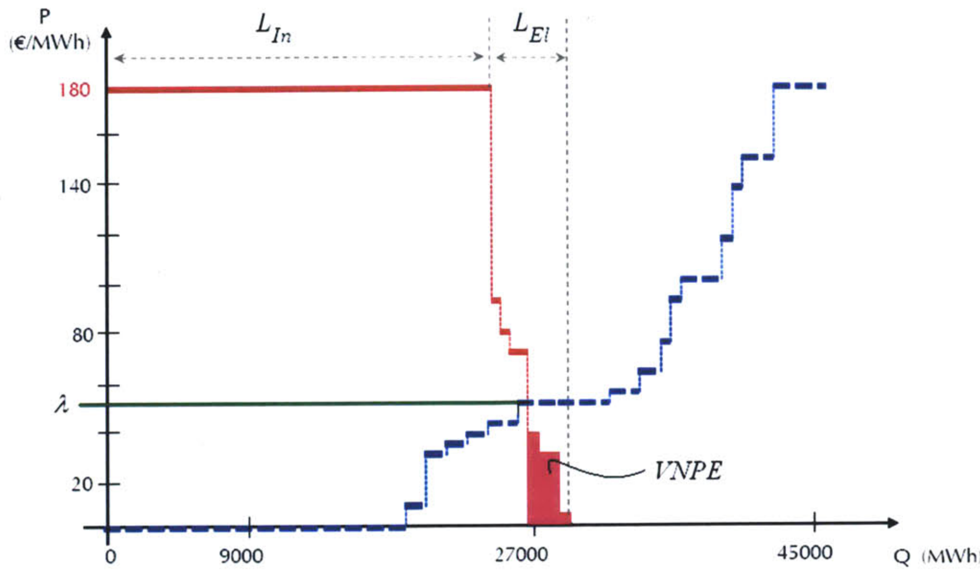

Figure 18: Graphical representation of the value of non-purchased energy (Rodilla & Batlle, 2011)

Formally, given a demand curve $D(Q)$, market clearing quantity q^*, and total quantity of energy demanded $\bar{q}$, the VNPE can be defined as

$$\int_{q^*}^{\bar{q}} D(Q) \cdot dq$$

Practically speaking, this is an easy integral to calculate since the quantity of each demand bid which did not clear the market can be multiplied by its bid price. The sum of these products is the VNPE.

The VNPE Distribution Function

Since we are dealing with random variables, the value of non-purchased energy calculated with the PPC model will not be a certain outcome but rather a probability distribution function of possible values of non-purchased energy. It is this distribution function which could be used as a supplement to the traditional generation adequacy metrics of LOLP and ENSE.

In order to calculate the distribution function of the *value* of non-purchased energy, first the distribution functions of the quantity of non-purchased energy are determined for each demand bid. These can then be multiplied by the bid prices to obtain the value of non-purchased energy probability mass functions for each fictitious generator. Finally, the sum of these probability mass functions will approximate the probability distribution function of the VNPE. Details of these calculations can be found in Ayala (2011). The proposed metric of VNPE is shown conceptually in Figure 19. Market outcomes could be compared to some benchmark distribution function, represented by standard values such as the mean of the distribution function or measures of the Value-at-Risk (Rodilla, 2010).

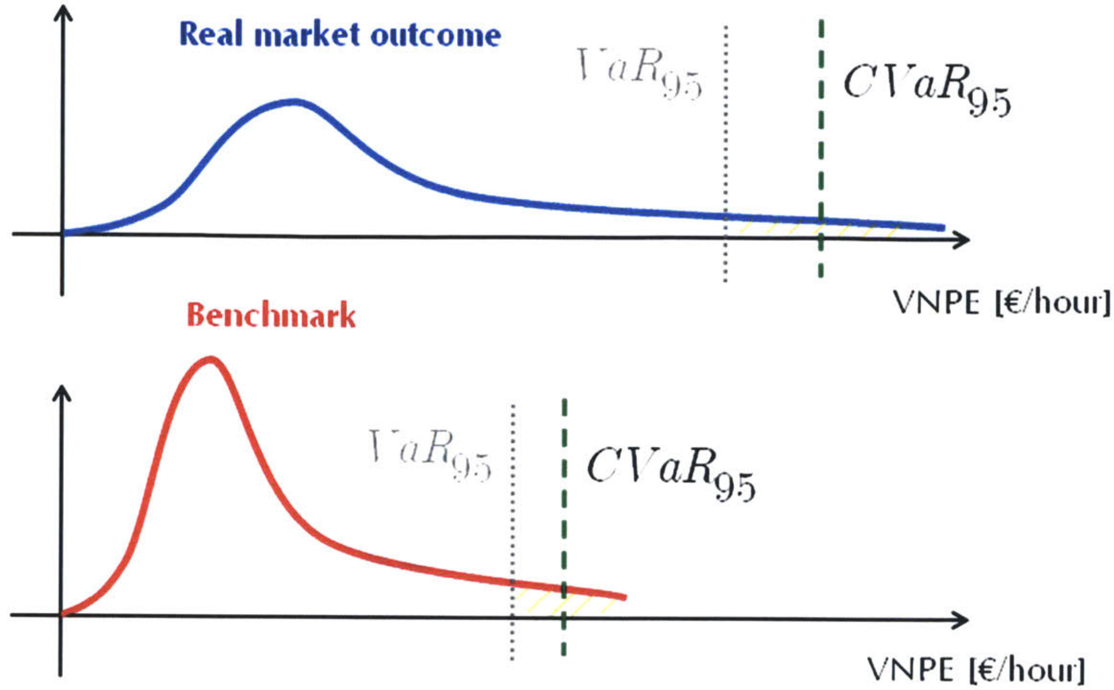

Figure 19: The VNPE distribution function could be used as a metric for market performance when demand elasticity is a factor (Rodilla & Batlle, 2011)

3.2 A Clustering Algorithm to Address the Time Dimension

Supply and demand bid curves change in every hour of real-time electricity markets according to the needs and strategies of the bidders. As inputs to the PPC model, demand bids will be translated into fictitious generators. PPC models assume that the set of generators will be the same in an entire period of study, and therefore we cannot account for the time-varying nature of the demand curve within the PPC framework presented in the last section. In order to include demand elasticity in the PPC model, we must arrive at a single elastic demand curve representing the entire period of study before turning to the PPC model. For this task, it is appropriate to think of clustering algorithms.

It is not quite true that we must come up with only a single elastic demand curve in order to use the PPC model. In fact, we can run the PPC model multiple times considering different periods. These periods can represent different blocks of hours within a single chronologically linked period of study. For example, we may want to run a PPC model to determine the LOLP of a particular system over one year. We could either do a single PPC model run considering all the hours of the year, or we could do two PPC model runs, each considering some subset of the hours in the year. These subsets do not need to be chronologically linked (i.e. the first three months and the last nine months) because the PPC model does not recognize chronology. Instead, we could divide the year into, for example, weekends and weekdays, nights and days, etc. In order to obtain appropriate results, after the separate PPC model runs are complete they are combined using an average weighted by the number of hours in each run.

This is a straightforward process; however, the question remains as to what is the best way to divide up the period of study. The more divisions, the more computationally intense, and the basic advantages of the PPC model are lost. So ideally, we would like to represent the overall period of study in a relatively small number of subperiods taking advantage of similar characteristics of time-varying elements: most importantly, the demand bids. A clustering algorithm is a very appropriate way to explore data, finding the more appropriate ways of dividing the overall period of study into subperiods.

3.2.1 Background

Clustering algorithms are a form of unsupervised learning, in which some set of empirical data is grouped into subsets called clusters so that similar data are paired together (Aldenderfer & Blashfield, 1984) . Of course, there are many dimensions along which data can be compared, so the definition of 'similar' is one of the central questions of clustering. In Figure 20, the dots represent data points which have been grouped into three clusters according to their distance from other data points.

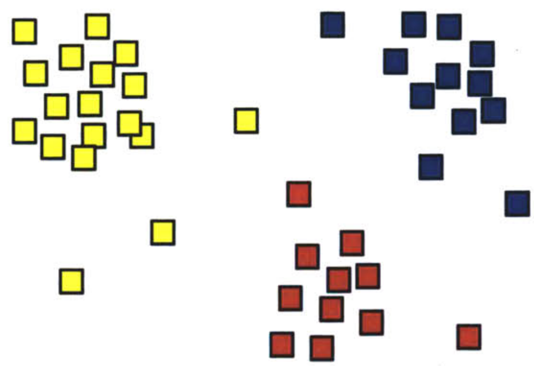

Figure 20: Results of a basic clustering analysis, clusters grouped by color (Ayala, 2011)

In fact, all clustering algorithms decide upon some measure of 'distance', even if the distance represents another concept. Clustering algorithms attempt to find structure in data sets which do not necessarily have structure; this makes them very appropriate in our search for patterns in bid data. The goal in obtaining representative clusters in a data set is to aid in the overall interpretation of the data, realizing that there is a loss of detail inherent to the process. A variety of clustering algorithms can be found in Romesburg (2004).

3.2.2 Clustering Elastic Demand Curves with the Neural Gas Algorithm

As mentioned in the introduction to Section 3.3, the PPC framework requires that elasticity be uniform across every hour in the simulation period. Therefore, our goal is to use a clustering algorithm to help us separate the hourly demand bids into clusters within which demand elasticity is more nearly uniform than when the whole set of data is considered at once.

The Neural Gas algorithm attempts to find feature vectors which are optimal representations of a data set. Clustering a group of curves into a single cluster results in a feature vector which is in some sense an 'average' of a group of curves; just as the average of a group of numbers is a simplified representation of those numbers, so too is a single feature vector a simplified representation of a group of curves.. Using more than one cluster to represent the group of curves results in more than one feature vector; the feature vectors, collectively, can be thought of as a simplified representation of the group of data.

The algorithm begins by guessing randomly, and iterates to find more appropriate feature vectors based on the specified measure of distance. The algorithm was introduced by Martinetz & Schulten (1991) and is named Neural Gas because the feature vectors resemble gas distributing through in space as they iterate through the data set.

Details of the iteration steps of the Neural Gas clustering algorithm particular to this application can be found in Ayala (2011).

Optimal Number of Clusters

The number of clusters which best represents a set of data has been the subject of much study (Sugar & James, 2003) (Fraley & Raftery, 1998). However, choosing the optimal number of clusters remains something of an art; the best method depends on the underlying, often unknown structure of data; the clustering method; and the desired effect of clustering.

In general, more clusters will result in less total clustering error. That is, separating a data set will usually allow a more accurate representation of the data through those clusters. However, we should not forget that the goal of using a clustering approach to create a simpler version of the data to help us understand broader trends. In the extreme case, we can imagine having a number of clusters equal to the number of data curves, with each cluster perfectly representing a single curve. In this situation we would have zero clustering error, but we would be no closer to determining any underlying themes in the data.

Qualitative comparison

This tradeoff can be illustrated with an example using elastic demand bid data. In Figure 21, a group of elastic demand curves (in yellow) are represented by a single 'feature vector' elastic demand curve (in green), determined using the Neural Gas algorithm. By visual inspection, it appears as though this data set might be separated into two relatively distinct groups, and the single feature may not be enough to represent this group of elastic demand curves. A better choice in this case might be two feature vectors (the second in red) as shown in Figure 22.

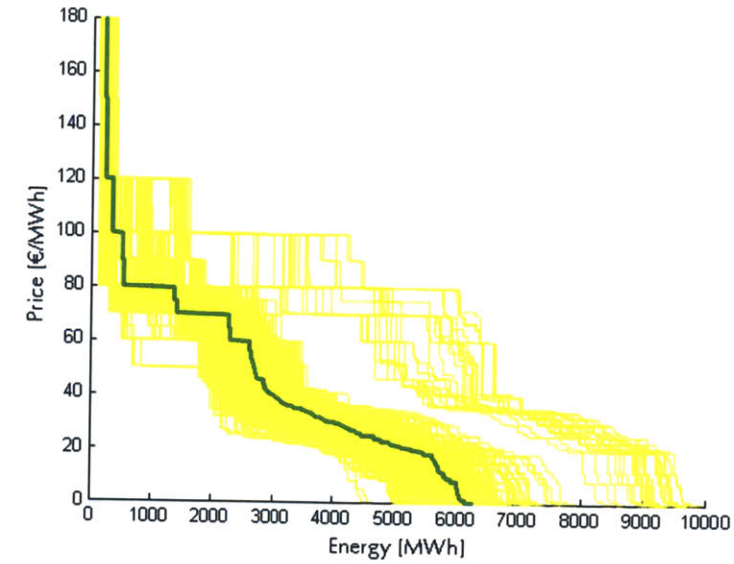

Figure 21: Elastic demand curves represented poorly by a single feature vector (Ayala, 2011)

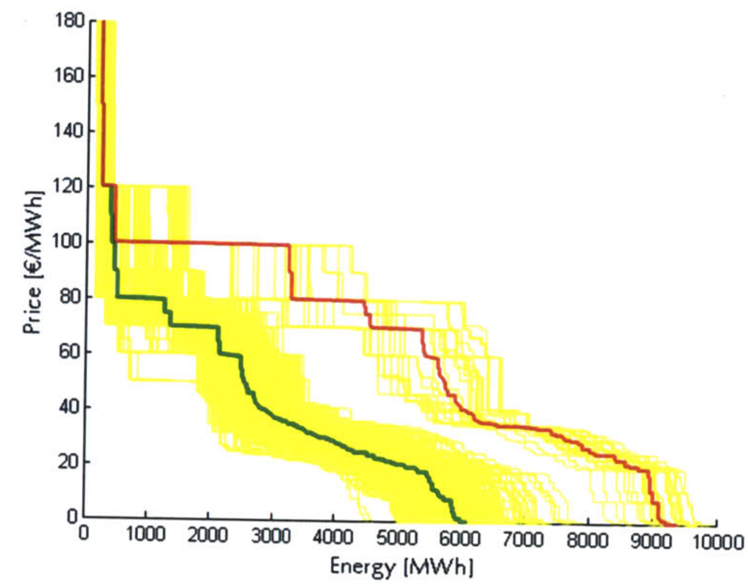

Figure 22: Elastic demand curves represented better by two feature vectors (Ayala, 2011)

The data in Figure 21 and Figure 22 appears to be well represented by two feature vectors. The same group of elastic demand curves is shown in Figure 23 represented by three feature vectors. Adding the third feature vector might increase the accuracy of the representation, or it might not. In any case, visual inspection indicates that the increase in accuracy of three feature vectors as opposed to two feature vectors will not be as great as the increase in accuracy of two feature vectors as compared to a single feature vector.

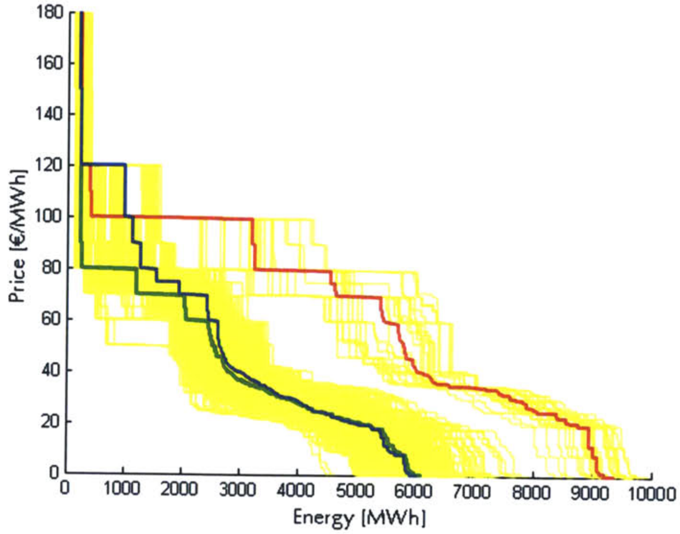

Figure 23: Elastic demand curves represented by three feature vectors. (Ayala, 2011)

a. Quantitative comparison with the elbow method

One more rigorous approach to determining the optimal number of feature vectors is the Elbow Method (Long, Zhang, & Yu, 2010). In order to use this method, we must first define a more precise measure of error in clustering. Our measure of distance, presented in Section 3.3.2, provides a basis for this error measure.

We first define the 'distance' measure used for the Neural Gas algorithm as the area between two demand curves, as shown in as shown in Figure 24.

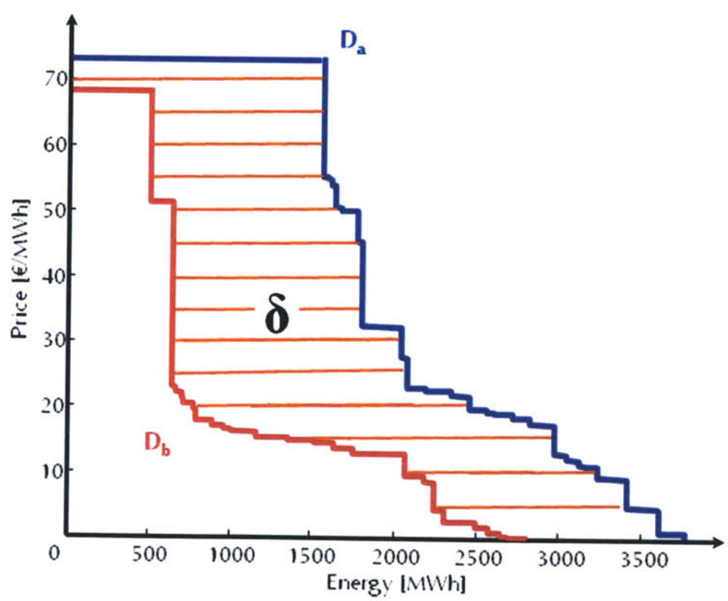

Figure 24: The distance measure chosen for the Neural Gas algorithm is the area between curves (Ayala, 2011)

The error measure we will use is the sum of the 'distances' (areas) between each original elastic demand curve and its closest feature vector. Formally, if the area between Γ demand curves $D_i = \{D_a, D_b \dots D_\Gamma)$ is called δ (as in Figure 24), and the feature vectors are denoted as F_j, then the total representation error (TRE) is defined as:

$$TRE = \sum_{i=1}^{\Gamma} min_j \delta(D_i, F_j)$$

With this quantitative measure of clustering error in mind, we can return to the example given in the previous section. There, we saw qualitatively a decreasing marginal benefit of adding more feature vectors. The Elbow Method for choosing the optimal number of feature vectors tell us that we should select the number of feature vectors where this marginal benefit begins to decrease. We can now define the marginal benefit formally as the change in TRE as we increase the number of feature vectors under consideration to include the α^{th} feature vector:

$$\Delta TRE_\alpha = \frac{TRE_{\alpha-1} - TRE_\alpha}{TRE_{\alpha-1}}$$

Table 2 shows the change in TRE as the data presented in the last section is represented with one, two, three, and four feature vectors.

	#1 Cluster	#2 Cluters	#3 Clusters	#4 Clusters
TRE [€]	3,728E+07	2,989E+07	2,901E+07	2,867E+07
ΔTRE [%]	-	19,82%	2,96%	1,17%

Table 2: Clustering error and change in clustering error representing data using one, two, three, and four feature vectors (Ayala, 2011)

A graphical representation, and the reason for calling this the Elbow Method, can be seen in Figure 25. In this case, according to the Elbow Method the number of feature vectors resulting in the most optimal mix of accuracy and simplicity would be two, just as our qualitative assessment in the last section concluded.

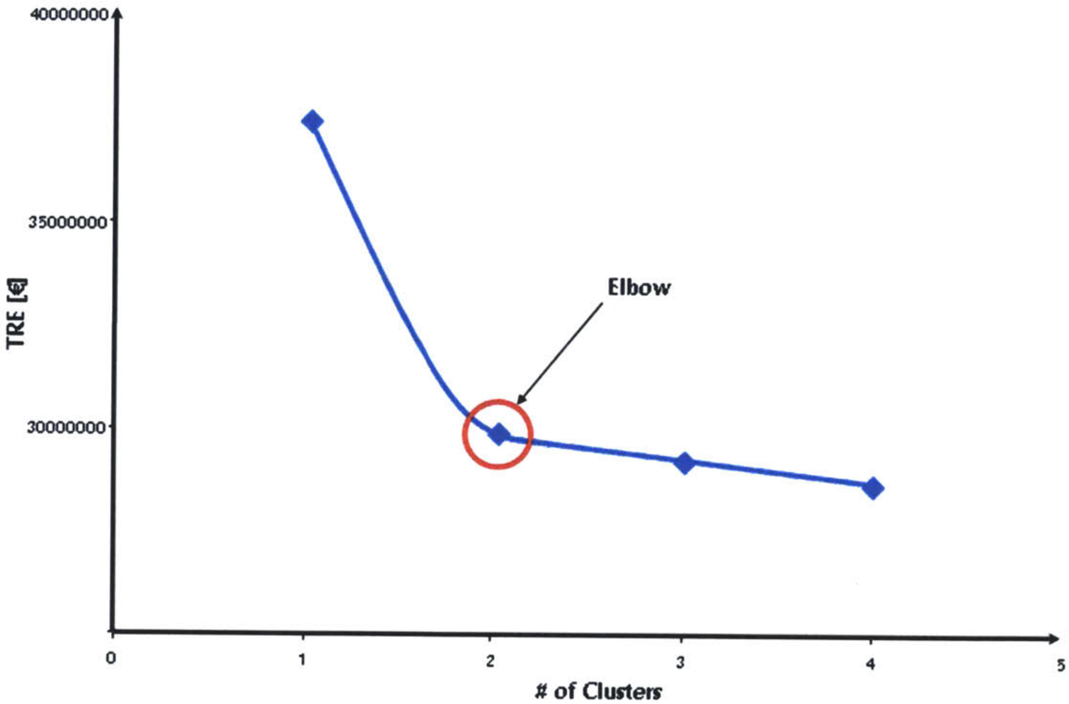

Figure 25: Illustration of the change in total representation error with different numbers of feature vectors (Ayala, 2011)

3.3 Conclusions

In this section, we have first described the basic probabilistic production costing model which can be used to calculate reliability measures such as LOLP and ENSE for a power system which is composed of thermal generators. We have also discussed a recent innovation to this model which allows the consideration of demand elasticity by treating demand bids as fictitious thermal generators in the PPC model.

We have also discussed the Neural Gas algorithm. In order to illustrate the concept, we have in the last section applied the clustering algorithm to the elastic portion of demand curves; however, the concept extends to clustering supply curve data. If we have full information about generators, it is unnecessary to use the clustering techniques on the supply side, since we can simply use the true set of generators. However, if this information is not known then the clustering algorithm can also be helpful in estimating the single set of generators to use in the PPC model. Thus, the Neural Gas algorithm can be used to cluster supply and demand curves from different hours in a longer time period (days, weeks, or months) into representative 'feature vectors'. We have also presented one method of choosing the appropriate number of feature vectors with which to represent a given data set of curves.

In the next section, the Neural Gas algorithm will help us select appropriate representative demand and supply curves for data in the New England power system. Then, the modified PPC model will be applied to determine the effect of ignoring elastic demand in reliability calculations, both under present system conditions and under various scenarios of future demand participation.

4 Case Study: New England's Power System

In this section, we will carry out a case study of New England's power system. Following a general description of the relevant features of New England's power system, including markets, generation capacity, and demand response programs, we will describe how fixed demand, elastic demand, and generation in New England will be modeled in the PPC framework. We will also develop a scenario of New England in the future, when demand elasticity will likely have an increased role compared to today. We will use these two scenarios of demand elasticity in New England to show the effect of considering demand elasticity on traditional reliability metrics, and how new metrics will be needed to cope with the shortcomings of LOLP and ENSE in a market setting with significant demand participation.

4.1 Description of New England's Power System

The New England power system is operated by the New England Independent System Operator (ISO-NE). ISO-NE is a regional transmission organization serving the six states of Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont. ISO-NE's role can be summarized in three primary responsibilities:

- Ensure the minute-to-minute reliability (security) of the New England power system by dispatching generation and performing studies to ensure transmission constraints and contingencies are properly handled.
- Administer New England's wholesale electricity markets.
- Manage regional planning of the bulk power system.

After a brief overview of markets administered by ISO-NE, we will delve into a more detailed look at those aspects of New England's power system which are relevant to the task of modeling this system in a PPC framework.

4.1.1 Markets

The New England market was originally established in 1999, the first in the country to operate completely based on market rates. The market design was updated in 2003 to basically its current form called the Standard Market Design. Major changes at this time were the establishment of a day-ahead market and improved locational pricing. The Standard Market Design was modeled after a structure previously used by Mid-Atlantic states (ISO-NE, 2010c) and is approved by FERC. Under the design, ISO-NE acts as both the system operator and the market operator.

From a legal standpoint, the Energy Policy Act of 1992 and the Energy Policy Act of 2005 both include provisions to encourage competition in markets for electricity. The Energy Policy Act of 1992 "encouraged FERC to foster competition in the wholesale energy markets through open access to transmission facilities." (FERC, 2010) The Energy Policy Act of 2005 "reaffirmed a commitment to competition in wholesale power markets as national policy."

Below the Energy Policy Acts passed by Congress, the secondary document describing New England wholesale electricity markets is Market Rule 1 (ISO-NE, 2011f). ISO New England is responsible for running the markets and does so in accordance with the reliability standards of NERC, the Northeast Power Coordinating Council (NPCC), and the ISO. Market participants include energy purchasers, generally called Load Serving Entities (LSE) or distribution utilities, and energy resources. 'Resource' primarily refers to generation resources, but also can mean demand side resources which offer to reduce energy demand in exchange for compensation. From the perspective of the ISO, responsible for balancing load with generation, these demand side resources are analogous to generation resources.

The ISO runs several markets which together ensure the proper operation of the power system. These markets include:

- *Day-ahead energy market*: By 12:00 noon on the day ahead, buyers and sellers of energy submit their estimates of the next day's load/energy needs and energy available, respectively, for each hour of the next day. Transactions for energy external to the New England system must also be specified. The prices calculated based on these bids include losses and congestion components. Bids are complex. Data must be provided by generators about the characteristics of the generator, such as ramping capability. Start-up and no-load fees are included in bids. The energy generation and market price are determined using the bids and security constrained optimal load flow. The day-ahead market also allows for virtual bids, financial instruments that allow market participants to hedge risk. Speculators may also participate and provide liquidity.
- *Real-time energy market:* This market exists to correct the imbalances in the energy commitments set in the day-ahead market. The market clears every five minutes on the operation day. It is based on an optimal load flow. The ISO calculates the price of energy at nodes and in load zones based on locational marginal prices. Locational marginal prices are calculated on the day ahead as well as every five minutes during the operating day for the real-time energy market. Losses and congestion are calculated explicitly. Day-ahead locational marginal prices for energy are calculated based on the unit commitment and economic dispatch and the prices of energy offers and bids. Real-time locational marginal prices for energy and real-time reserve clearing prices are calculated based on a jointly optimized economic dispatch of energy and designation of operating reserve. These calculations also utilize the prices of energy offers and bids, as well as penalty factors.
- *Forward Reserve Market:* The purpose of the forward reserve market is to secure ten minute non-spinning reserves and thirty minute operating reserves. These reserves are secured during two yearly time windows, winter and summer. Auctions for the reserves are held two months before each season starts.
- *Forward Capacity Market:* In addition to the day-ahead and real-time energy markets, there is also a forward capacity market which occurs yearly and secures the installed generator capacity requirement set by the FERC for the region for the year three years ahead of the auction. Bilateral agreements between energy suppliers and loads are permitted.
- *Financial Transmission Rights:* This market allows suppliers of energy to hedge the costs of delivering power over transmission lines that may be congested.

The analysis later in this section derives information from several of these markets: the day-ahead energy market, the real-time energy market, and the forward capacity market. The forward reserve market and financial transmission rights will not be discussed further.

It should be noted that all of the ISO-NE markets have a locational element; prices are not set uniformly across the entire region, but differentiate by node and by zone. In the case of the day-ahead and real-time energy market, this is reflected in the locational marginal prices at the different zones. Location matters as well in other markets; for example, the forward capacity market contains special 'local sourcing requirements' which ensure that local as well as regional resource adequacy goals are met.

Despite the importance of location in New England's markets, the PPC model used in this analysis will treat the entire New England region in a uniform manner, not differentiating between zones or nodes. This simplification is made for the sole reason of making the problem tractable within the scope of this master's thesis, but future work could extend the model to differentiate between zones.

4.1.2 Fixed Demand

ISO-NE is a summer-peaking system, meaning that the annual system peak is experienced during the summertime, generally on one of the hottest days of the year. The annual peak loads in ISO-NE are shown in Figure 26. Blue data points are the actual system peak loads in each year, while the red line tracks the peak loads normalized for weather. The red line gives a more accurate idea of the trend of load growth in the region, while the blue points show the real demand on the system resources each year.

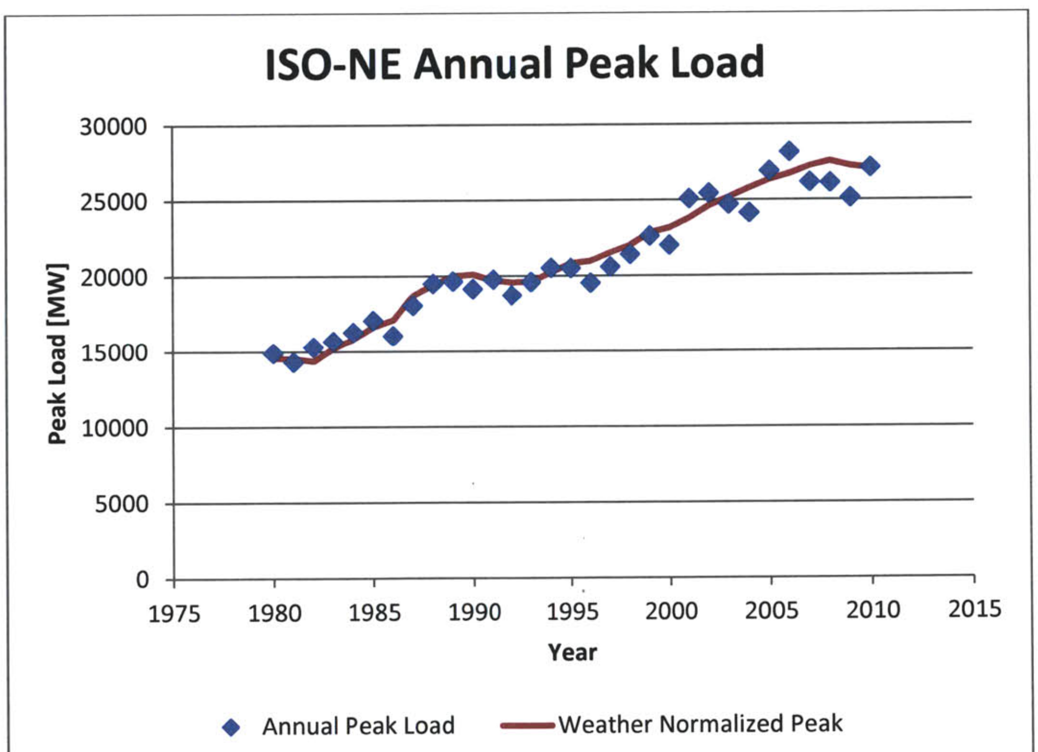

Figure 26: ISO-NE annual peak loads (ISO-NE, 2011a)

Figure 27 shows the load data for the year from March 2010 to February 2011, the most recent data available at the time of writing. The system peak in this year occurred on July 7th, 2010 at 3:00pm. The winter peak was much lower than the summer peak and occurred on January 23rd, 2011 at 5:00pm. The load duration curve shows plainly the typical characteristics: maximum system capacity is only required for a very small fraction of the hours of the year, requiring peaking plants to serve in just those few hours.

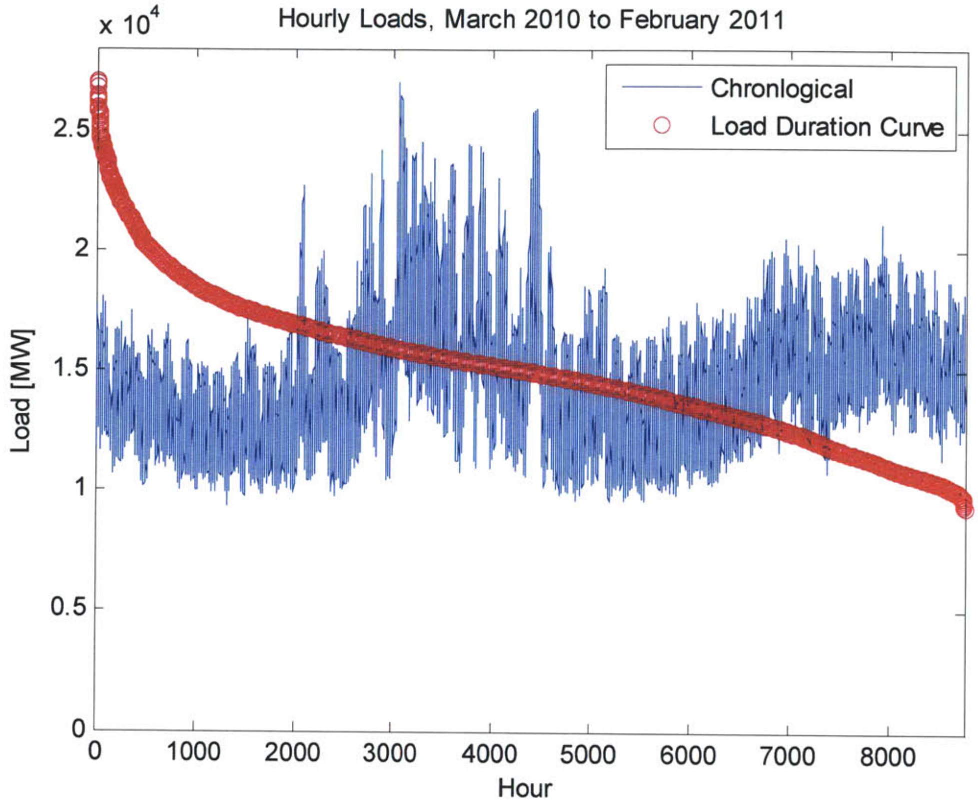

Figure 27: ISO-NE Hourly loads for the year from March 2010 to February 2011 (the most recent data available) (ISO-NE, 2011c)

4.1.3 Generation

Measures of System Capacity in ISO-NE

ISO-NE generating capacity is generally measured as the Seasonal Claimed Capability (SCC) defined in Market Rule 1: "Seasonal Claimed Capability is the summer or winter claimed capability of a generating unit or ISO- approved combination of units, and represents the maximum dependable load carrying ability of such unit or units, excluding capacity required for station use." (ISO-NE, 2011e)

Seasonal claimed capability is used to determine how much capacity generators are allowed to bid into the forward capacity auction. However, it is not the maximum possible output of generators under all conditions. In addition to seasonal claimed capability, ISO-NE also records the Network Resource Capability (NRC) and the Capacity Network Resource Capability (CNRC) as part of the Interconnection Agreements found in Schedule 22 and 23 of the Open Access Transmission Tariff (ISO-NE, 2011e). These represent the maximum seasonal outputs of generating units under the following conditions: NRC is measured at 0 °F in the winter and 50°F in the summer, while CNRC is measured at 20 °F in the winter and 90 °F in the summer. As expected, aggregate system NRC is larger than the CNRC, which is larger than SCC. The 2010 ISO-NE summer and winter SCC, NRC, and CNRC are listed in Table 3.

	Summer [MW]	Winter [MW]
Seasonal Claimed Capability (SCC)	**29260**	**32577**
Capacity Network Resource Capability (CNRC)	**33235**	**35812**
Network Resource Capability (NRC)	**34429**	**36079**

Table 3: System capacity for ISO-NE in 2010, measured by SCC, NRC, and CNRC

Because SCC represents the maximum dependable load carrying capability of a unit, we will follow the standard practice of using this value as the system capacity. In the PPC model of ISO-NE we will base our representation of system supply on the Seasonal Claimed Capability values. We will use class average forced outage rates for each unit. However, in order to determine the merit order of the generating units we will have to make assumptions about average variable costs. As explained in the following sections, the variable costs of each unit will be estimated by comparison to real-time energy offer data.

Generation Mix

The Seasonal Claimed Capability by unit type for New England is shown in Table 4. The information pertaining to the summer Seasonal Claimed Capability in Table 4 is shown graphically in Figure 28. The New England generation mix is dominated by natural gas combined cycle generation. Coal also contributes significantly, although at well below the national average. Nuclear also has a significant presence. Wind is still very small in New England, with only 26 MW projected on peak capacity in 2011 (NERC, 2010), though this amount is expected to grow. Solar is nonexistent. Wind and solar resources are not shown in the Seasonal Claimed Capability quantities because of the New England rules pertaining to intermittent resources.

ISO-NE Seasonal Claimed Capability by Unit Type				
	Winter [MW]	Winter [%]	Summer [MW]	Summer [%]
Combined Cycle Total Unit	13106	40%	11421	39%
Fossil	8811	27%	8890	30%
Nuclear	4674	14%	4629	16%
Hydro (Run of River, Weekly, and Pumped Storage)	2984	9%	1826	6%
Combustion Gas Turbine	2790	9%	2283	8%
Internal Combustion Engine / Jet Fuel	213	1%	211	1%
Total	32577		29260	

Table 4: Seasonal Claimed Capability of New England in 2010 by unit type

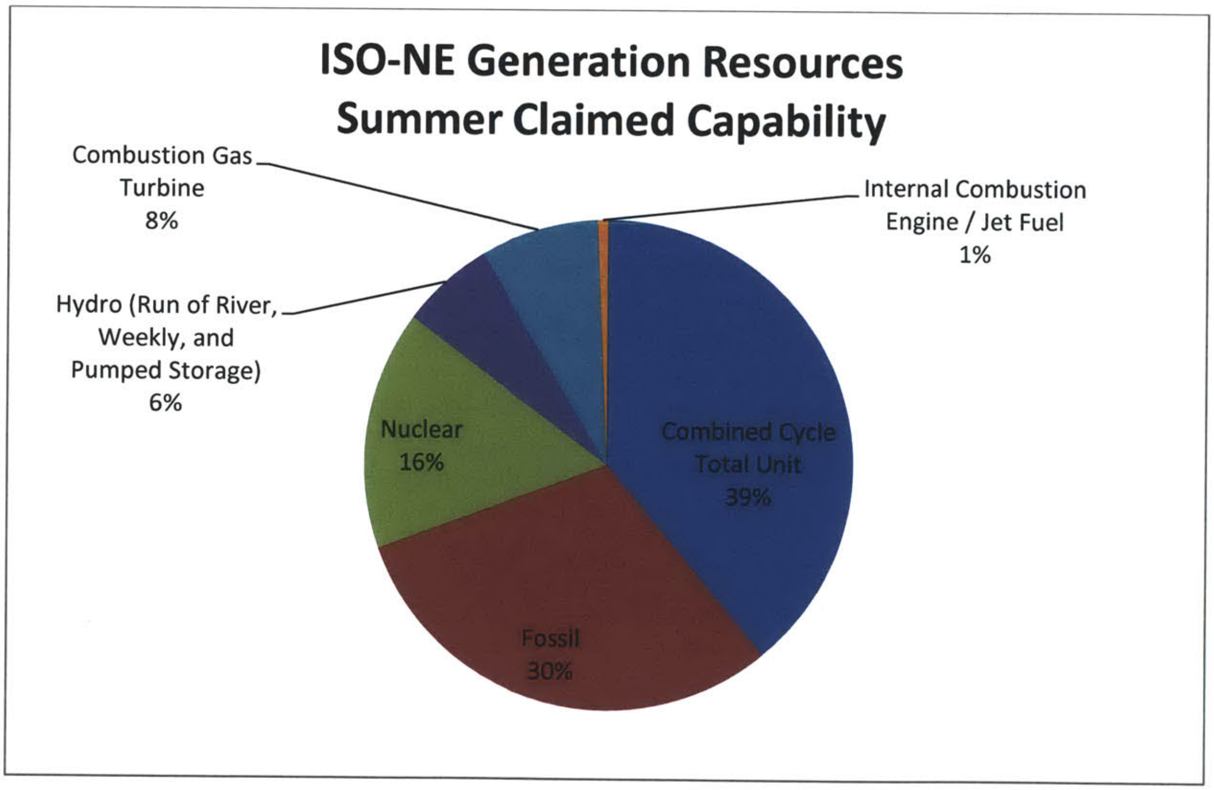

Figure 28: Summer Seasonal Claimed Capability in New England 2010

Overcapacity in ISO-NE

ISO-NE does not lack for generation resources; the reserve margins in ISO-NE are well above the NERC reference margin and are expected to grow even more until 2012 before falling off slowly over the next eight years, as shown in Figure 29. The situation of overcapacity in ISO-NE will influence the output of the PPC model; we can expect to see very low LOLP and ENSE values.

Figure NPCC-2: Summer Peak Reserve Margin Projections

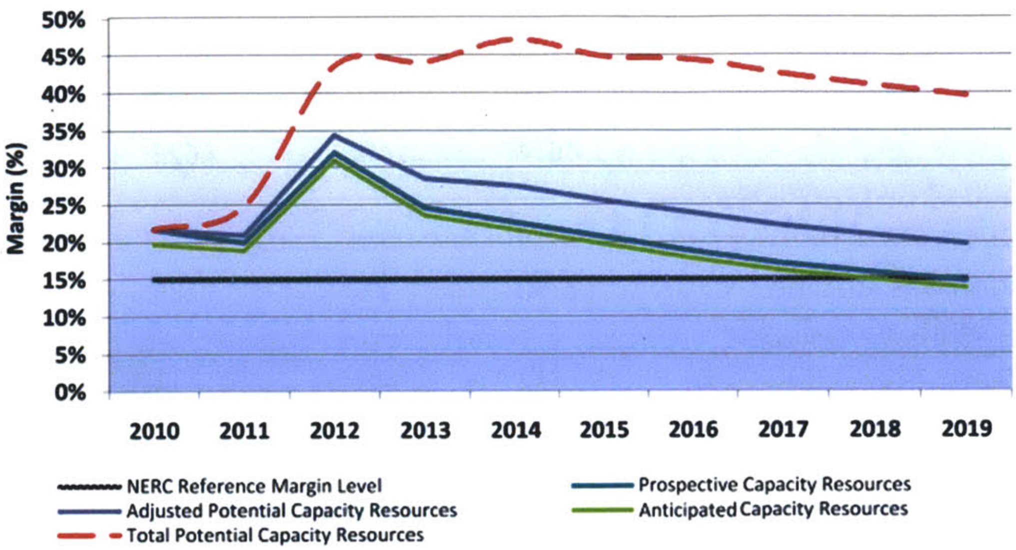

Figure 29: NERC projected reserve margins in ISO-NE to 2019 (NERC, 2010)

4.1.4 Demand Participation

In ISO New England, some demand is able to participate directly in the wholesale market by submitting bids in the day-ahead market. A variety of programs offer other opportunities for demand to become active. In this subsection, we will describe these opportunities for demand participation.

Direct participation in the day-ahead market

Market participants (primarily Load Serving Entities, but also some very large individual customers) may submit bids in the day-ahead energy market and thus participate directly in the wholesale electricity market. These participants contribute directly to demand elasticity, composing the portion of the day-ahead market demand curve which is downward-sloping.

In the PPC model, these direct participants in the day-ahead market will be modeled in a straightforward manner according to the method described in Section 3.1.2. Each demand bid will become, in the model, a fictitious generator included in the convolution operation.

Other demand response programs

In addition to the LSEs and few large customers that bid directly into in the day-ahead energy market, there are a variety of demand response programs in New England which allow compensation for demand reductions in various forms. These programs include Real-Time Price Response (RTPR); Real-Time Demand Response (RTDR); Real-Time Emergency Generation (RTEG); On Peak Demand Resources; Seasonal Peak Demand Resources; and the Day Ahead Load Response Program (DALRP). These programs are summarized and categorized in Figure 30, and will be described in more detail below.

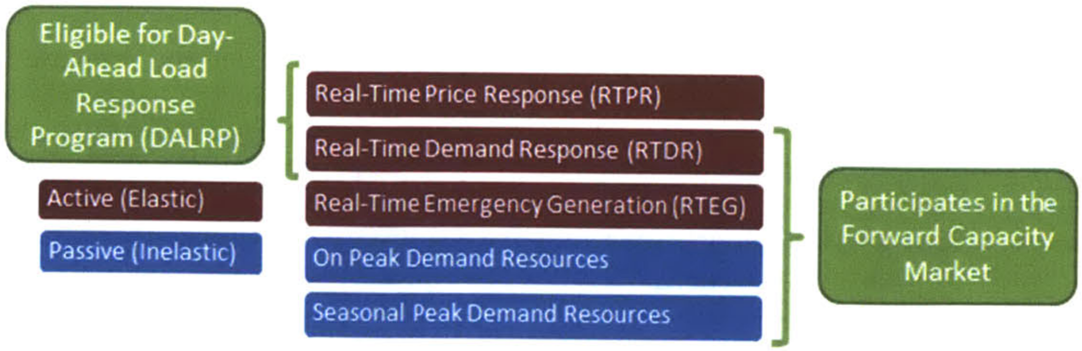

Figure 30: Summary of demand response programs in ISO-NE

Figure 31 shows the level of participation (in MW) in these demand response programs for the year from June 2010 to May 2011. Here, we can see that the RTDR and RTEG programs make up the bulk of the active demand response programs. We also see that the participation in the DALRP is drawn from other demand response programs. The volume of participation in the DALRP is therefore not added to the total. DALRP participants are drawn from loads already enrolled as RTDR or RTPR (ISO-NE, 2011b).

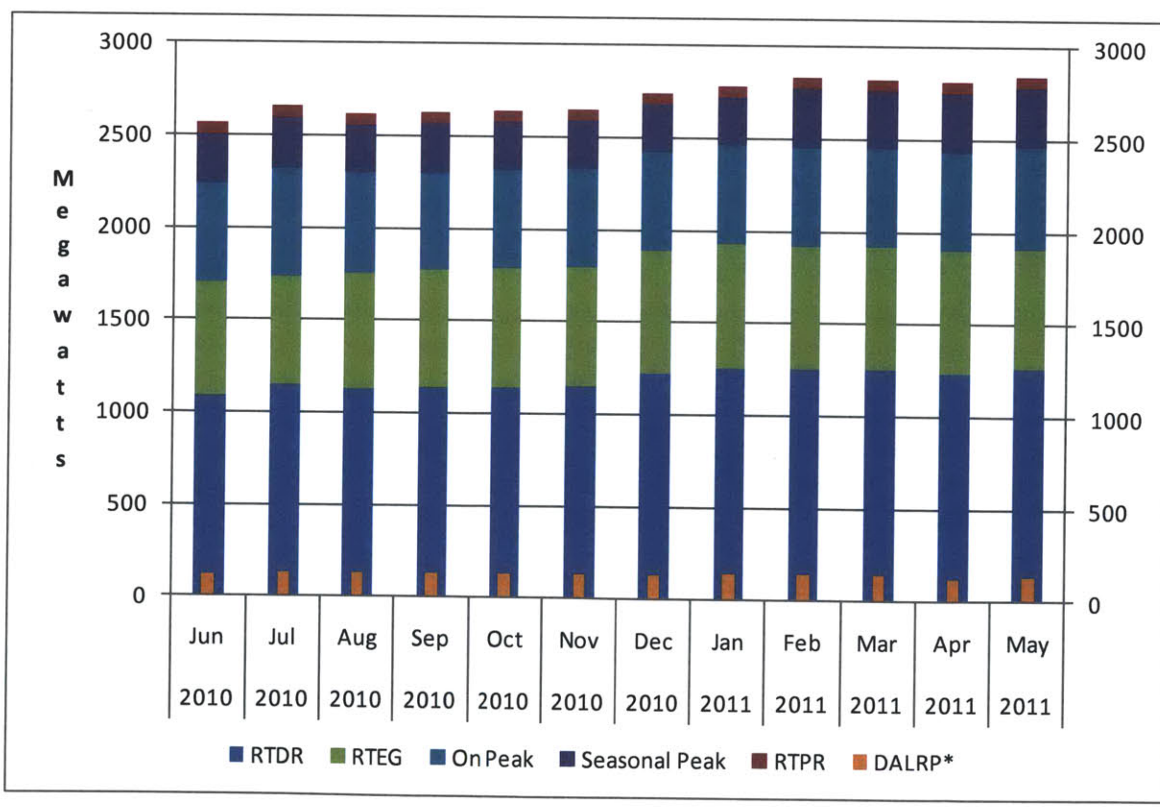

Figure 31: Participation in New England demand response programs (ISO-NE, 2011b)

Real-Time Price Response

Real-time price response (RTPR) is unique among the New England demand response programs in that it does not participate in the Forward Capacity Market. Customers must participate in this program with at least 100kW of responsive demand. Participants are notified of specific 'price response days', which are triggered in part by a day-ahead forecast indicating that market prices in the following day will reach higher than $100/MWh. On these price response days, participants are compensated when they reduce electricity consumption below their baseline level of consumption. If the price in the wholesale market is above $100/MWh, participants are compensated in the amount of the full market price. If the price is below $100/MWh, then customers receive $100/MWh for their reductions.

The real-time price response program is currently the only price-responsive demand program in New England, and participation levels are currently extremely low, as shown in Figure 31. The rest of the programs described here are either triggered by reliability concerns rather than a price signal, or are simple energy efficiency programs which are eligible to participate as capacity in the forward capacity market.

Though currently the portion of demand response programs based on price is very small in New England, the FERC Order No. 745 may lead to a rule change very soon which requires demand response resources to be compensated at the wholesale market price. This would trigger a shift in the type of demand response programs offered at New England. Though the form which these new programs might take is not public information, stakeholder talks are under way. Given the nature of Order No.745, it seems likely that any new demand response programs would be based more on market prices than reliability.

Real-Time Demand Response

The real-time demand response (RTDR) program offers retail electricity customers the chance to participate in the forward capacity market. In this program, consumers agree to make themselves available for demand reductions when system operators implement Operating Procedure 4 (OP-4) Action 6 or higher, or when this operating procedure is forecasted to be necessary in the following day. OP-4 is the operating procedure describing what to do in the event of a capacity shortage; in addition to calling on demand response resources, it also includes steps such as issuing news updates and asking neighboring interconnections for help. OP-4 is triggered based on the expert judgment of the ISO that capacity is in short supply; it is not directly linked to wholesale market prices (though shortages generally do go hand in hand with high market prices). Participants in this program are compensated through capacity payments and not based on the wholesale market price.

Real-Time Emergency Generation

Real-time emergency generation (RTEG) is similar to RTDR in that it is triggered based on OP-4. The difference is that RTEG participants are behind-the-meter generators and special rules apply to their participation in the forward capacity market. However, from an operational perspective the two are essentially identical.

RTDR and RTEG make up the bulk of the active demand response programs in New England (see Figure 30 and Figure 31). These reliability-based demand response programs do not respond to price, but do have a similar effect on system operations, relieving strain when it is most critical.

On Peak Demand Resources

On-peak demand resources are a passive demand resource, which means that they are unresponsive to signals and are primarily composed of energy efficiency measures implemented on loads such as motors and lighting. These resources are allowed to participate in the forward capacity market as long as it is demonstrated that the fixed reductions will occur at times of 'on-peak' hours, defined in the summer as 1-5pm during July and August non-holiday weekends and in the winter as 5-7pm on December and January non-holiday weekends. On-peak demand resources are also a significant fraction of the total demand response programs in New England, making up roughly one fifth of the total (see Figure 31).

Seasonal Peak Demand Resources

Seasonal peak demand resources are similar to on-peak demand resources in that they are fixed and do not respond to signals from the system operator of any kind. Seasonal peak hours are defined as hours when demand is forecast to reach 90% of the seasonal peak load forecast. Measures aimed to reduce energy consumption of weather-sensitive loads such as energy efficient heating and air conditioning systems are the most common participants in this program, also part of the forward capacity market.

Fixed demand resources are not appropriate to include in the PPC model as elastic demand since they are fixed and their effect is reflected in the historical load data used to determine the LCDF.

4.1.5 Reliability calculations for planning

As mentioned in Section 4.1.1, the Forward Capacity Market is the mechanism through which the New England ISO ensures adequate capacity to maintain a reliable and efficient system. The Forward Capacity Market is implemented as a declining clock auction wherein market agents offering capacity resources make quantity bids at progressively lower prices until only the desired amount of capacity remains. The auction closes when supply no longer exceeds demand.

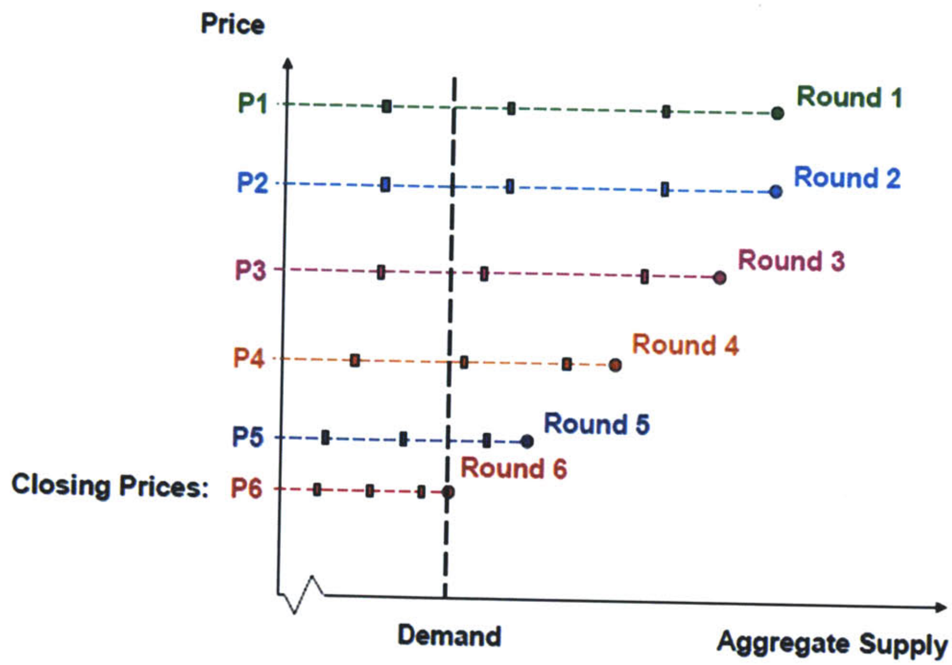

Figure 32: New England Forward Capacity Auction (Ausubel & Ashcroft, 2007)

The task of ISO-NE in preparing for the auction is to decide how much demand is required in order to meet goals for system reliability (i.e., to meet the one day in ten years criterion). This is done through calculation of an Installed Capacity Requirement (ICR). Demand in the Forward Capacity Auction is determined as the amount of additional capacity resources, beyond what is already available, needed to meet this ICR.

All details of the method of ICR calculation are not public, but the NE-ISO does explain in broad strokes the elements which go into the calculation and the general method of solution. Essentially, a reliability model is used to assess the level of reliability of the system – in other words, to calculate the system LOLE – based on current expected capacity resources. If these resources result in an LOLE which is more than one day in ten years, then resources are added until LOLE drops below the threshold.

The reliability model used is not a PPC model (ISO-NE, 2011d). Instead, New England uses a sequential Monte Carlo simulation. Similar to the PPC model, this method also takes into account randomness in load and resources. Monte Carlo simulation requires more computational power than a PPC approach, but it is also more flexible. Variables accounted for in the ISO-NE reliability model include:

- The possibility that load forecasts may be exceeded through variations in weather
- Forced outage rates
- Generating units scheduled outages
- Seasonal adjustments of resource capability
- Maintenance requirements
- Available operating procedures
- Reliability benefits of interconnections with neighboring systems

From this list, we can tell that many of the elements included in the ISO-NE Monte Carlo approach to calculating reliability metrics are similar to those included in the PPC model. Since details are not available it is difficult to give a nuanced comparison of the two approaches. However, we can see that just as in the PPC model, the ISO-NE model accounts for randomness of load levels as well as various sorts of generation outage possibility. Though we cannot say with absolute certainty, it also seems that interruptible demand response is also included in the calculation: 'available operating procedures' must refer to Operating Procedure 4 (ISO-NE, 2010b), which in turn specifies the general conditions under which demand side capacity resources may be called upon.

4.2 Representing New England in the PPC framework

Now that we have generally described the characteristics of the New England power system we will turn to the task of determining the appropriate representation of the New England power system within the PPC framework. As described more fully in Section 3.1.1, we will represent generators as binary random variables characterized by their full capacity value and forced outage rate. Fixed demand will be represented as a probability distribution by estimation using the historical system demand levels.

Fortunately, there is a significant amount of information publicly available describing the New England power system. However, this information is not the precise information necessary. We must therefore undertake an investigation to interpret the available data and determine the most appropriate representation of New England's generators in the PPC model

4.2.1 Generation

As described in Section 3.1.1 several pieces of information are required in order to model generators in New England:

- The capacity of each generator in the New England system
- The expected forced outage rate of each generator
- The merit order of the generators, preferably as the marginal operating cost

The capacity and marginal operating costs of generating plants make up the market's supply curve, and we will therefore talk about constructing the 'supply curve' for use in the PPC model.

Modeling hydroelectric generators is very difficult and outside the scope of this thesis, so we have the option of excluding New England hydroelectric generators from the model or including them as thermal generators. Hydro is an energy constrained resource as well as a capacity constrained resource, so some of the constraints on hydro are not reflected in the capacity-oriented PPC model. Including hydro in the model as thermal generation will bias the LOLP and ENSE outputs of the model by making the system appear more reliable than it truly is, since these units are energy constrained and treating them as thermal units removes the energy constraint. Excluding the hydro units altogether will introduce a bias by making the system seem less reliable than it truly is. Hydroelectric resources comprise 6% of summer claimed seasonal capacity. Since the capacity is not insignificant, the PPCM model would make generation appear very inadequate if hydro is excluded entirely. Therefore, the results will be more meaningful if the hydro is included despite the fact that it is being modeled incorrectly and introduces some bias making the system appear more reliable than it is.

We model New England in this thesis not to make specific recommendations pertaining to this system but rather to demonstrate the principles of demand response and reliability metrics and the challenges of applying the modified PPC model to a practical system. Therefore, the bias introduced by improperly modeling hydro generation is not of great concern.

Capacity of each generator in New England

Several values are made public which we might interpret as the capacity of each generator in New England. As described in Section 4.1.3, each large generator participating in New England markets must execute an agreement which specifies the Capacity Network Resource Capability (CNRC), the Network Resource Capability (NRC), or both. These represent the maximum capacity of the generator, each at different operating temperatures. Generators wishing to be compensated for their capacity value must participate in the forward capacity market; this subset of generators also undergo seasonal audits which result in a Seasonal Claimed Capability (SCC) of that generator representing the "maximum dependable load carrying ability" of that generator (ISO-NE, 2011e). In practice, most generators participate in the forward capacity market in order to receive the maximum possible compensation for their services. The SCC values of individual generators may be as high as their CNRC values, but not all are so high after the results of seasonal audits.

For the purposes of the PPC model, we will use SCC values, since these represent the dependable maximum capability of the system. The fact that SCC for individual generators may be lower than CNRC and NRC values does not reflect the forced outage rating of that generator as will be represented in the PPC model; rather, it reflects that the maximum capacity of a generator in a given season is not necessarily the capacity value that system planners studied before that generator joined the interconnection. Generators are also not required to join the capacity market with their full capacity with which they participate in daily markets, only the amount for which they wish receive compensation by dependable availability.

Forced Outage Rate

On the publicly available list of generators including the generator type and seasonal claimed capacity value, the individual forced outage rate of each generator is not included (though ISO-NE does record this information and use it within their own models). Instead, we will assign the class-average forced outage rates gathered by NERC and reported by ISO-NE based on the type of each generator (ISO-NE, 2010a). Generator classes and forced outage data given are shown in Table 5.

Marginal Operating Cost

The marginal operating costs of individual generators, from which we will derive their merit order, are proprietary information of generation owners and disclosed to ISO-NE. However, a close approximation is revealed by bids in the real-time (and day-ahead) wholesale market. In general across electricity markets, supply bids should represent marginal costs. The complex bidding structure of ISO-NE markets allows generators to bid startup costs separately from marginal energy costs. For our purposes, this means that the marginal component of ISO-NE generator bids in real-time and day-ahead markets is a good way to approximate the marginal costs of the generators.

Bids in the day-ahead and real-time markets are published publicly by ISO-NE, but published information does not reveal identifying information about the unit bidding. As a result, we choose to construct a generic 'supply curve' for New England by associating Summer Seasonal Claimed Capability of each generator with energy bids in the day-ahead and real-time markets. Since a reasonable approximation is all that is required, we assume that all of the units in a given class have the same marginal cost and construct the supply curve by visual trial and error. The results are shown in Table 5.

Generator Class	Expected Forced Outage Rate	Assigned Marginal Cost ($/MWh)
Combined Cycle	0.0588	40
Internal Combustion	0.07	400
Fossil	0.07	120
Combustion Gas Turbine	0.1	60
Hydro-Conventional Daily Pondage or Run of River	0.07	0
Hydro-Conventional Weekly	0.0363	0
Jet Fuel	0.1	200
Nuclear	0.02	0
Pumped Storage	0.0337	100

Table 5: Expected forced outage rates and assigned marginal prices by generator class

Note that the assigned marginal cost does not necessarily reflect the true marginal cost of each unit, especially since there are certainly great variations in the prices of different units within each class. Despite the considerable inaccuracy on an individual generator level, in aggregate, these assumptions lead us to a reasonable approximation of the true supply curve as observed in the hourly real-time and day-ahead market data. The results are shown in Figure 33.

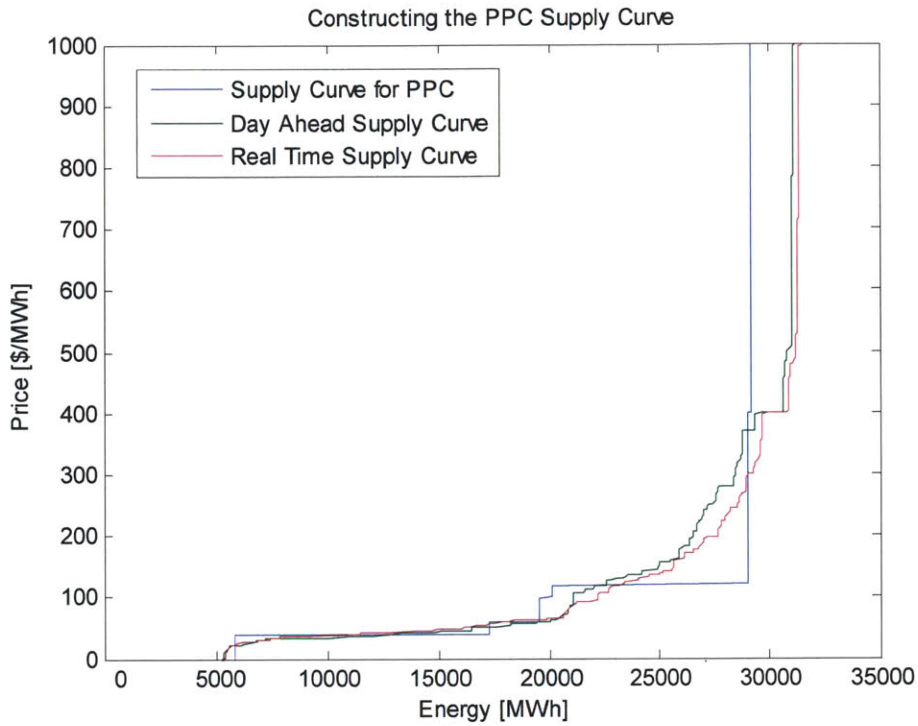

Figure 33: Comparison of supply curve used to represent New England in the PPC model with Real-Time and Day-Ahead hourly supply curves for July 7, 2010 hour of 3pm.

There is a small difference in the supply curves of the day-ahead and real-time markets reflecting forecasting errors and activities on the part of generator to hedge risks. However, the two are very similar. The supply curve labeled 'Supply Curve for PPC' was constructed as described above, using the Summer Claimed Capability values and trying marginal cost estimates for each generator class until the approximated SCC data matched the actual supply curves as closely as possible.

The difference in total bid quantity between the SCC-constructed supply curve and the actual market data bid curves is due to the fact that generators are not required to participate in the forward capacity market and receive a SCC capacity value (though most do). Those that do participate may not receive a seasonal capacity value as high as their CNRC/NRC capacity value. Thus, in any given hour, the actual supply bid quantity is greater than the "maximum dependable load carrying ability" (ISO-NE, 2011e) of the generators. It is the lower SCC values which is more conservative from the reliability planner's perspective. Because we have more information about the generator types in the SCC list, and the SCC values are more conservative, we choose to use these values to formulate a representative supply curve for New England for the PPC model.

Supply curve clustering

In the next section, we will discuss the use of a clustering algorithm to separate the chosen timeframe of study into different clusters of similar hours so that the condition of uniform supply and demand within a PPC model run is less problematic. By analyzing demand bid data, we choose to separate the time of study into four clusters of similar demand bid curves. Each of these clusters will represent a group of specific hours.

Despite having four separate demand curves representing each of these groups of hours, we choose to use only a single supply curve, as discussed above, in all of these groups of hours. In addition to the convenience of this tactic given the lack of information about individual generator forced outage rates in the supply bid data, we can also justify this simplification on the basis that supply curves are more tightly grouped across the period of study than demand curves; using a single representative curve across all periods introduces less error than would result if a single demand curve were used in the same way.

Figure 1 shows the clustering error for hourly demand and supply curves in New England from June 1 to August 31, 2010 clustered using the Neural Gas algorithm (see Section 3.2). Though the elbow test suggests that the optimal number of clusters is 2, we justify using only one supply curve to represent all periods by the observation that the magnitude of the TRE with only one cluster on the supply bids is approximately the same as the magnitude of the TRE for two clusters of the demand bids. This indicates that the supply curves are more tightly clustered than the demand curves.

Though curves are more tightly grouped on the supply side than the demand side, the elbow test still shows that two clusters would be preferable to one on the supply as well as the demand side. In other words, better results could be achieved by representing supply in two distinct periods, just as we do with demand. However, these periods are not the same for both supply and demand, making the choice of periods and representative curves considerably more difficult. Choosing optimal periods of study considering clustering results of both supply and demand curves is an interesting topic for future research.

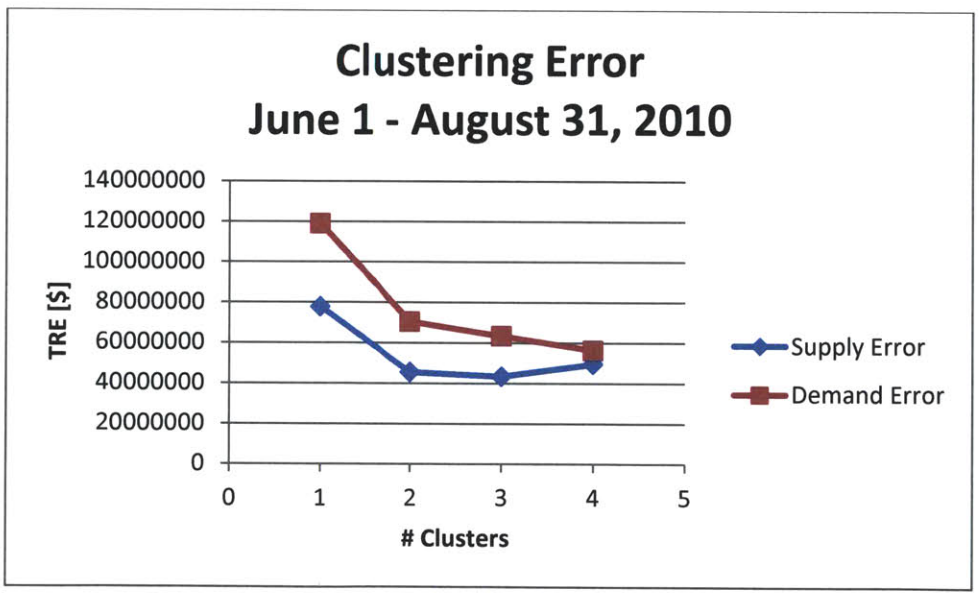

Figure 34: Clustering error for hourly demand and supply curves in New England from June 1 to August 31, 2010 clustered with the Neural Gas algorithm

In the next section on representing New England's demand in the PPC model, we will present more clustering results on the demand side and discuss the choice of periods to be used in the PPC scenario analysis.

4.2.2 Elastic Demand and Selection of Subperiods

As described in Section 4.1.4, the general description of demand participation in New England, there are two sources of demand elasticity in the region. The first is demand bids submitted in the day-ahead market by LSEs and some large individual customers. The second are demand response programs, primarily those through which customers participate as actively responsive capacity in the forward capacity market. In this section, we will first describe briefly exactly how each of the demand response programs described in Section 4.1.4 will be represented (or not) in the PPC model. We will then turn to a discussion of the demand curve formed by day-ahead demand bids, and how the time-variations in this demand curve will determine our selection of subperiods to study with the PPC model.

Demand elasticity from demand response programs

Real-Time Price Response

The real-time price response program is currently the only price-responsive demand program in New England, but participation levels are currently extremely low. Due to the very low participation, as shown in Figure 31, we will not include this category of demand response in the PPC model scenario. In the future, when price-responsive demand becomes a much larger part of New England's demand response programs, it can be incorporated in the model by inserting more demand bids as fictitious generators as additions to the day-ahead demand bids.

Real-Time Demand Response and Real-Time Energy Generation

Participants in the real-time demand response (RTDR) and Real-time emergency generation (RTEG) programs will be included in the PPC model as interruptible demand, as described in Section 3.1.2. The combined total combined capacity of these two programs is approximately 1900 MW, as seen in Figure 31 on page 53. This 1900 MW will be triggered when system reserves drop below 15%.

On Peak Demand Resources and Seasonal Peak Demand Resources

On-peak demand resources and seasonal peak demand resources are passive demand resources, unresponsive to signals from the NE-ISO. They will not be explicitly included in the PPC model. The reductions in demand achieved by these resources are already implicitly included in the historical demand levels which will form the LCDF of the demand random variable in the PPC model.

Demand elasticity in the day-ahead market

In the original PPC model, demand is represented by constructing the load complementary distribution function (LCDF) from historical load levels, assumed to be the distribution function of a random variable as described in Section 3.1.1. The modified model we use to represent the New England system has two additional complications. First, historical demand contains both a fixed component and a price-dependent component. Second, we divide the timeframe of study, in this case the summer of 2010, into several periods within which assumptions about uniformity of supply and demand in time are more acceptable, then combine the results of each period to obtain results for the whole summer. We will discuss each of these complications in turn, concluding by precisely defining the four subperiods which will be used in the New England PPC analysis and the representative elastic demand curves in each of these subperiods.

Resolving fixed and elastic demand from historical data

First, the demand curve contains both a fixed component and a price-dependent component. Historical loads as recorded by system operators are composed of the entire fixed component (except in extremely rare circumstances of load shedding), and the portion of elastic demand which cleared the market. Given that most demand bids are high relative to supply bids in New England and elsewhere reflecting the high value of energy compared to the cost of producing it, historical loads can be approximated as the sum of the fixed demand component and the elastic demand component.

This is not quite true; during times of very high prices, some demand bids do not clear the market. However, given the limited data available pertaining to the relationship between fixed demand bids, price dependent demand bids, and historical load levels in New England, we will settle for the approximation that historical load always includes all fixed demand bids and all elastic demand bids.

Choice of periods

Second, we must choose an appropriate time division of the summer of 2010 in order to reduce the error from the PPC-imposed assumption that demand and supply must be uniform in time. The requirement of uniform supply and demand stems from the convolution calculation, where fixed demand must be represented by a single random variable and generators and demand bids represented by a single set of binary random variables. To choose appropriate time periods, we will employ the Neural Gas algorithm as a clustering tool to gain information about the similarity of demand bids in different subperiods of the summer of 2010.

First, we apply the clustering algorithm to the entire summer of 2010. More precisely, we cluster elastic demand bid curves in the hours starting with the hour from 12:00am June 1st, 2010 and ending with the hour from11:00pm August 31st, 2010. We apply the clustering algorithm assuming one, two, three, and four clusters, comparing the clustering error of each in Figure 35.

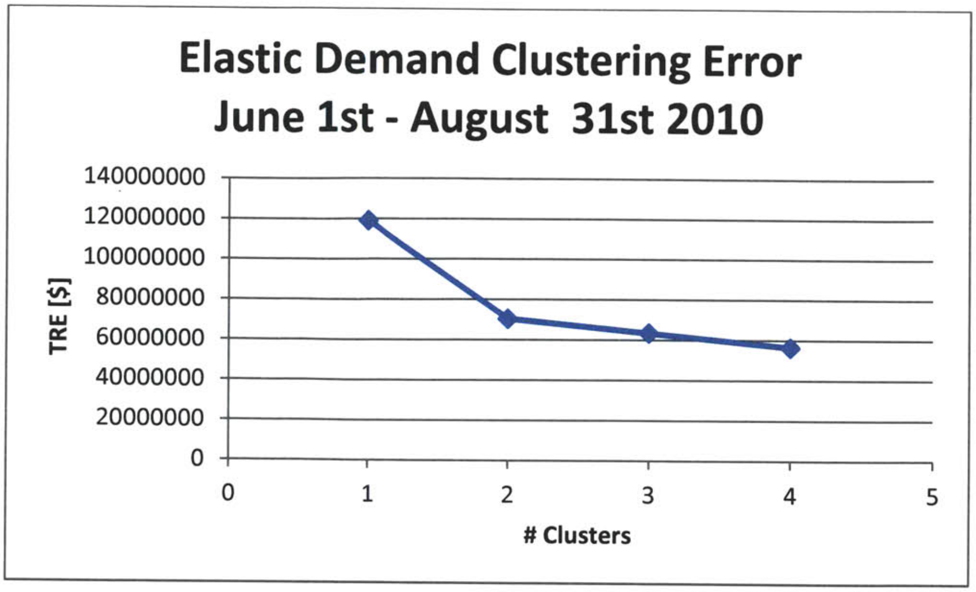

Figure 35: Clustering error for hourly elastic demand starting with the hour from 12:00am June 1st, 2010 and ending with the hour from 11:00pm August 31st, 2010

The elbow test shows that two clusters is a reasonable balance between the simplicity desired from clustering and the error introduced by clustering; thus, we examine the results of the Neural Gas algorithm more closely in the case of two clusters. Figure 35 shows the two feature vectors in blue; these are the best representation of the underlying hourly elastic demand bid curves shown in yellow.

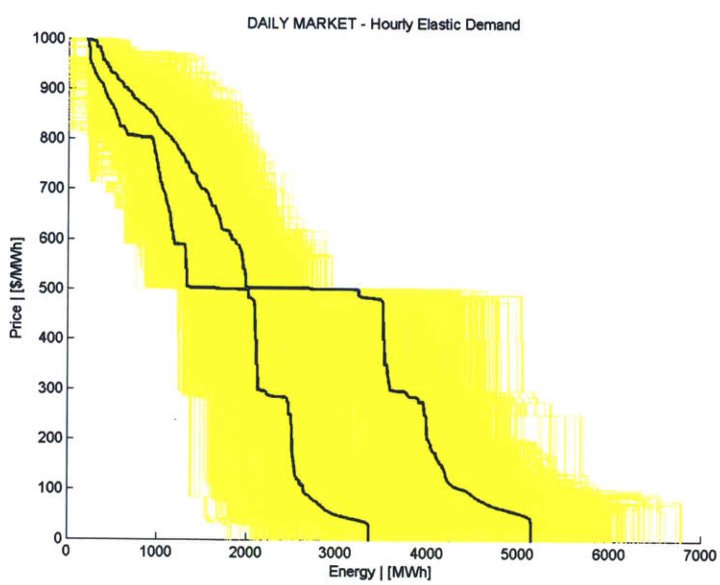

Figure 36: Representation of summer 2010 demand bids using two clusters

Next, we would like to know which hours within the period are represented by each feature vector. We do this by showing all of the hours of the period as a grid and using different colors for hours represented by each feature vector, as shown in Figure 37. In the figure, each row corresponds to one day of data and each column is one hour in that day. Viewed in this way, we can see that there is a pattern in the association of demand bid curves with each of the two feature vector demand curves. One cluster is generally composed of daytime hours in June, July, and part of August; the other is composed of nighttime hours plus weekends and some daytime hours in August. The pattern of bidding in August is generally different from the pattern of bidding in June and July.

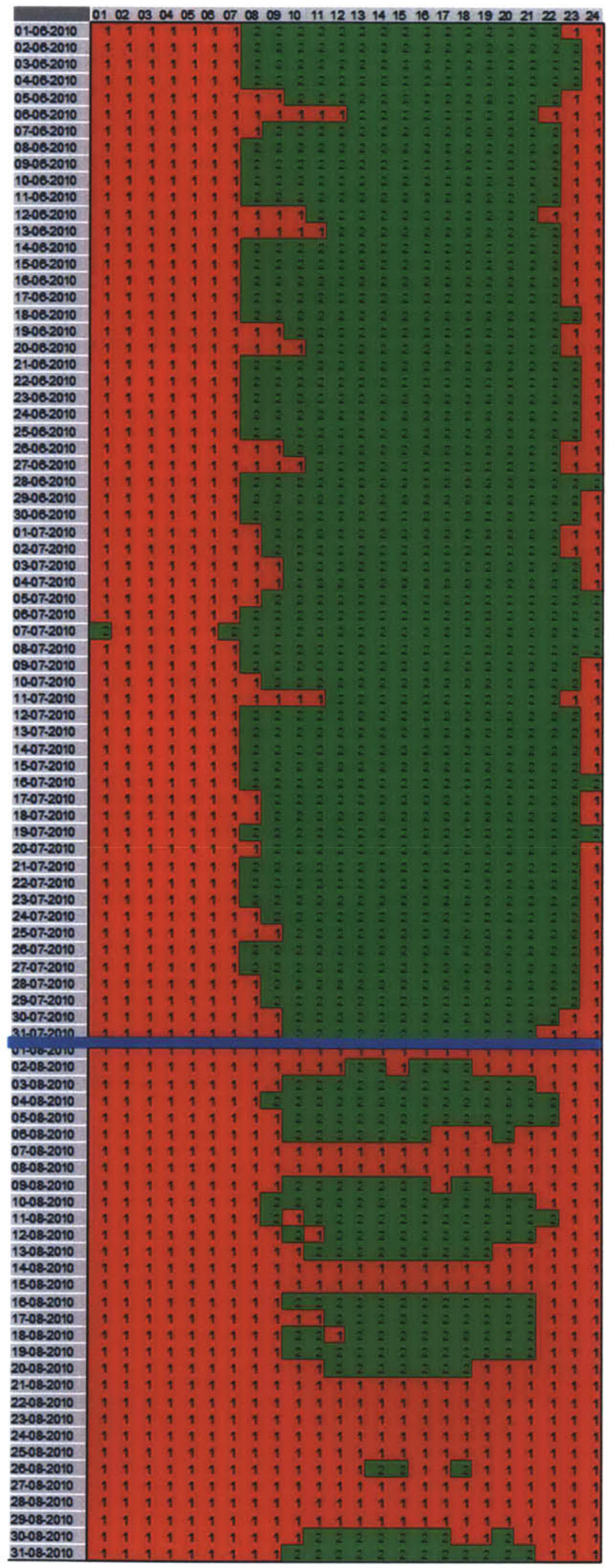

Figure 37: Association of summer 2010 hours with each of two elastic demand bid clusters

Since our goal is to obtain a set of uniform subperiods within the period of study, we first choose to split the three months into two groups, one containing June and July and the other containing August. This division is shown with the blue line in Figure 37. Then, we again apply the Neural Gas algorithm to demand curves in each of these subperiods using one, two, three and four clusters. Clustering errors in each subperiod are compared in Figure 38 and Figure 39.

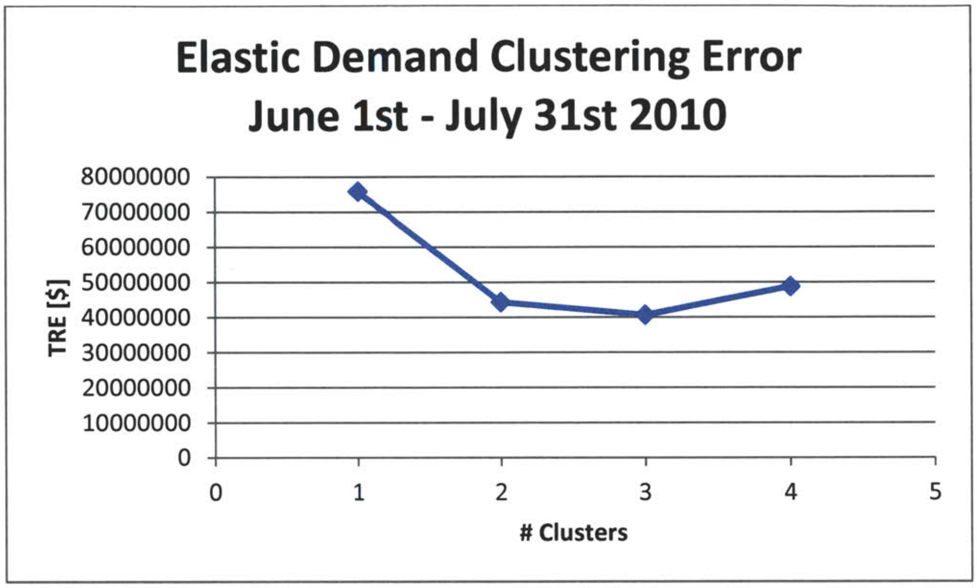

Figure 38: Clustering error for hourly elastic demand starting with the hour from 12:00am June 1st, 2010 and ending with the hour from 11:00pm July 31st, 2010

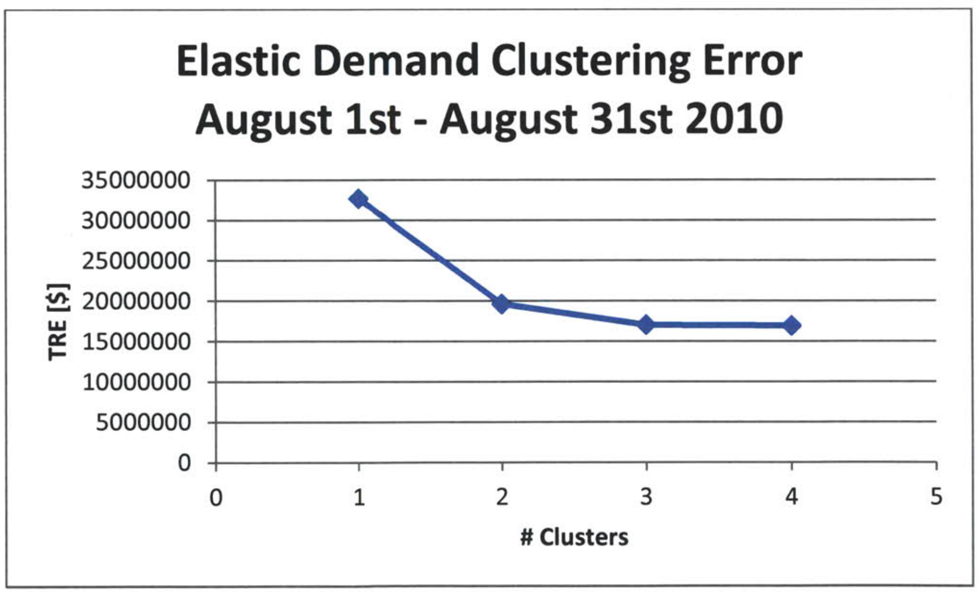

Figure 39: Clustering error for hourly elastic demand starting with the hour from 12:00am August 1st, 2010 and ending with the hour from 11:00pm August 31st, 2010

The pattern of error across different numbers of clusters in these two subperiods is essentially the same as we have seen; using two clusters to represent the underlying curves is a sweet spot. One other interesting trend in the error for the two month period from June to July can also be seen in Figure 38. Clustering error decreases when the number of clusters used to represent the data increases from one cluster to two and again from two clusters to three; then, when the demand curves are represented using four clusters, the error actually increases. This allows us to go one step further than the elbow test, a quantitative method of finding a reasonable balancing point between simplicity and accuracy of representation, and say that in this case using four clusters would be unequivocally worse (not only less simple but also less accurate) than three or even two clusters.

Following the suggestion of the elbow test, we will choose to represent each of these subperiods with two clusters. To determine the associations of the clusters with hours in these periods, we again place the hours in each subperiod on a grid and color the hours associated with each cluster differently. Results for June – July clustering are shown in Figure 40 and for August in Figure 41.

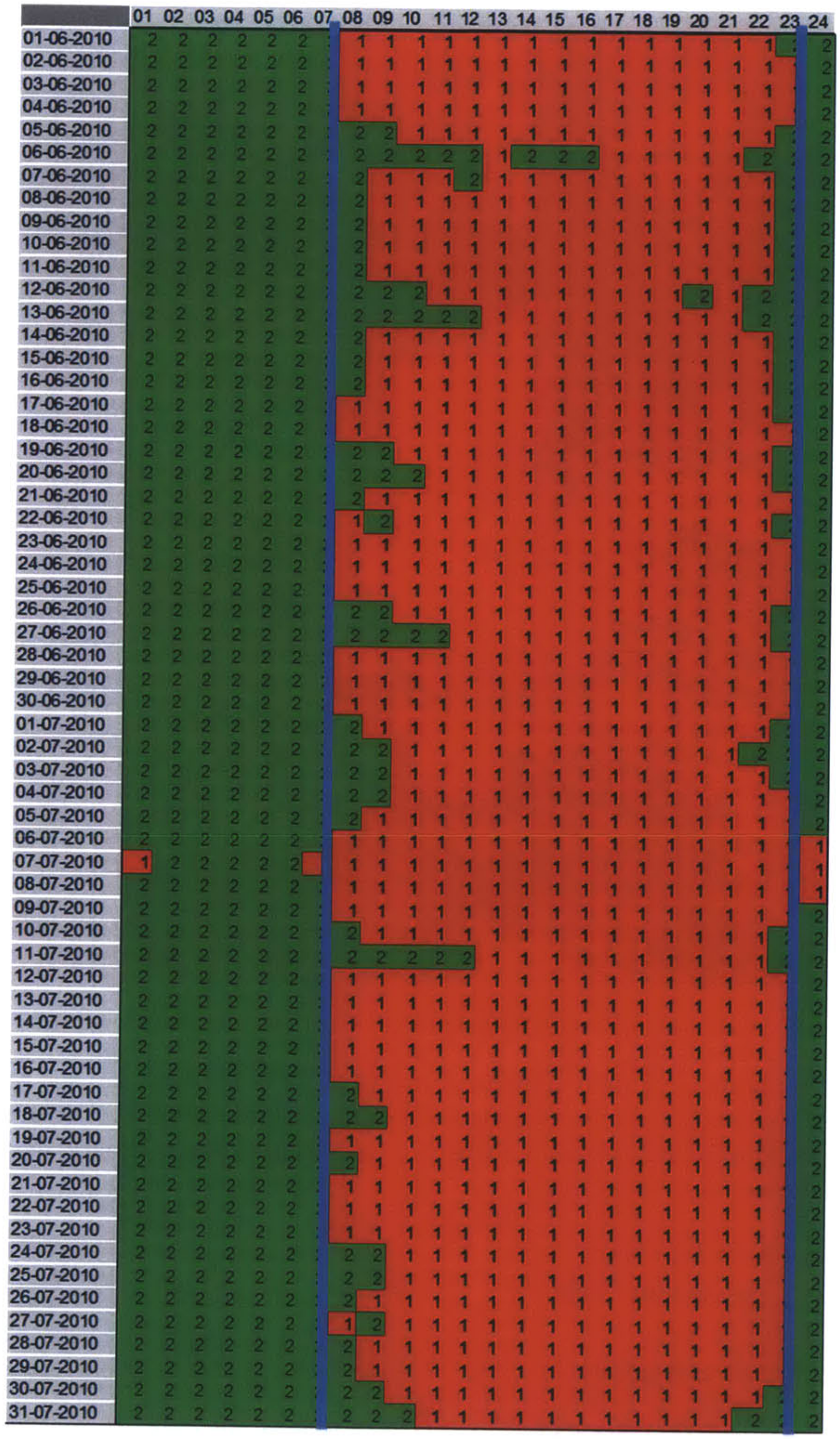

Figure 40: Association of June - July hours with each of two elastic demand bid clusters

	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
01-08-2010	2	2	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	1	2	2	2
02-08-2010	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2
03-08-2010	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2
04-08-2010	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2
05-08-2010	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2
06-08-2010	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2
07-08-2010	2	2	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	1	2	2	2
08-08-2010	2	2	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1	2	2
09-08-2010	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2
10-08-2010	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2
11-08-2010	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2
12-08-2010	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2
13-08-2010	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2
14-08-2010	2	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1	2	2	2
15-08-2010	2	2	2	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	1	2	2
16-08-2010	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2
17-08-2010	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2
18-08-2010	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2
19-08-2010	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2
20-08-2010	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2
21-08-2010	2	2	2	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	2	2	2
22-08-2010	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
23-08-2010	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2	2
24-08-2010	2	2	2	2	2	2	2	2	1	1	1	2	1	1	1	1	1	1	1	1	1	2	2	2
25-08-2010	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2	2
26-08-2010	2	2	2	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	1	2	2
27-08-2010	2	2	2	2	2	2	2	2	1	2	1	2	1	1	1	1	1	1	1	1	1	2	2	2
28-08-2010	2	2	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	1	2	2	2
29-08-2010	2	2	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1	2	2
30-08-2010	2	2	2	2	2	2	2	2	1	2	1	1	1	1	1	1	1	1	1	1	1	1	2	2
31-08-2010	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2

Figure 41: Association of August hours with each of two elastic demand bid clusters

Now that the whole summer data is separated into two subperiods, we can see that within each period the pattern of daytime and nighttime clusters holds in both cases. We are now close to arriving at a reasonable representation of the original summer hourly elastic demand data in four distinct clusters of hours:

- daytime hours in June/July
- nighttime hours in June/July
- daytime hours in August
- nighttime hours in August.

We could choose to leave the periods as they were chosen by the clustering algorithm, with most but not all daytime hours in each subperiod represented by a single cluster. However, for the sake of simplicity in the final choice of periods, we will clearly divide each of the subperiods into two clusters as denoted by the blue lines in Figure 40 and Figure 41. Within each of these subperiods we will again apply the Neural Gas algorithm to represent each of these groups of hours with a single feature vector elastic demand curve.

The results shown in Figure 42 are the final representations of elastic demand in the four subperiods which will be used as inputs to the PPC model for the New England power system.

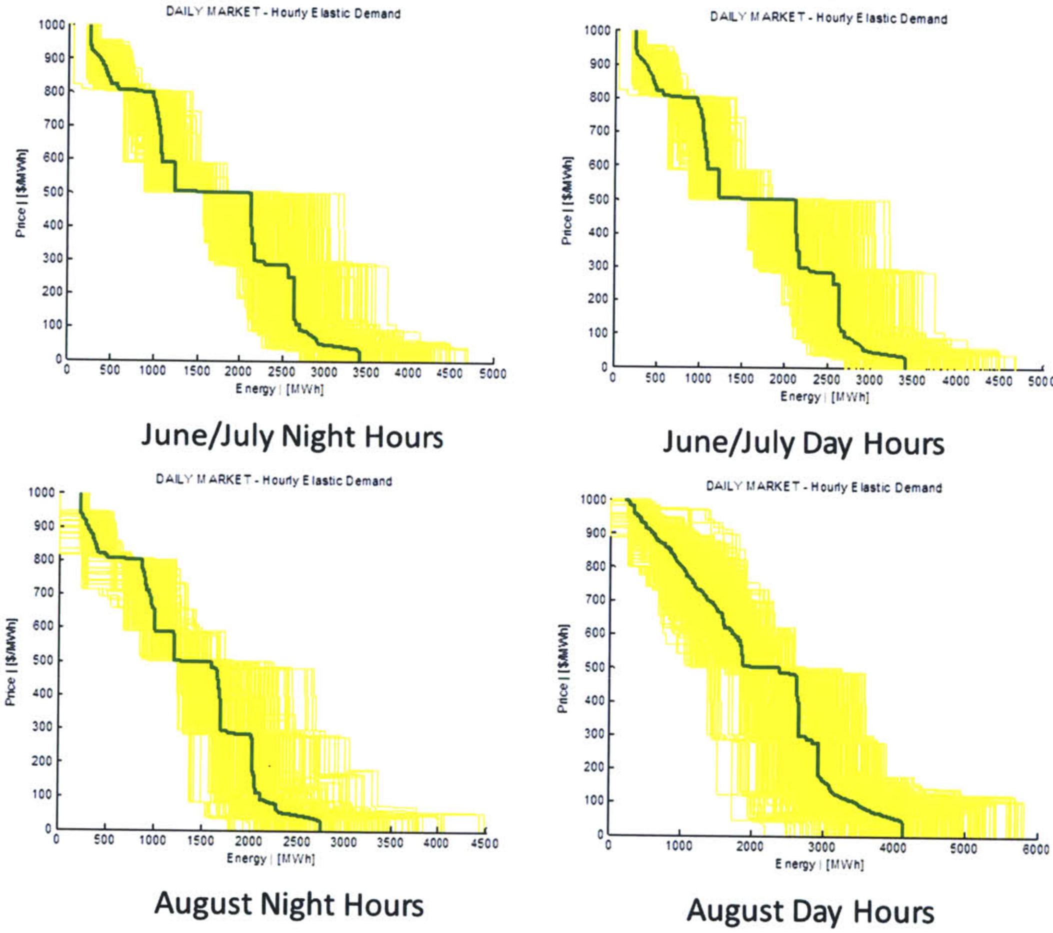

Figure 42: Elastic demand curves for final choice of subperiods and feature vectors representing each

The four chosen subperiods represent hours of similar demand bidding. Though we are justified in choosing these four clusters for the similarities in the demand bid data in these hours, we might still ask why these periods are distinct from one another. The day/night distinction is relatively intuitive. It makes sense that bidders would have different preferences during daytime hours, when demand is relatively high and industrial and commercial facilities are running, than nighttime hours, when demand is low and industrial and commercial facilities are generally closed. However, the source of the discrepancy between the June/July block of hours and the August block of hours is less intuitive. As shown in Figure 43 and Figure 44, an analogous separation of June/July from August can be seen in neither the daily peak temperatures nor the daily peak loads during the period.

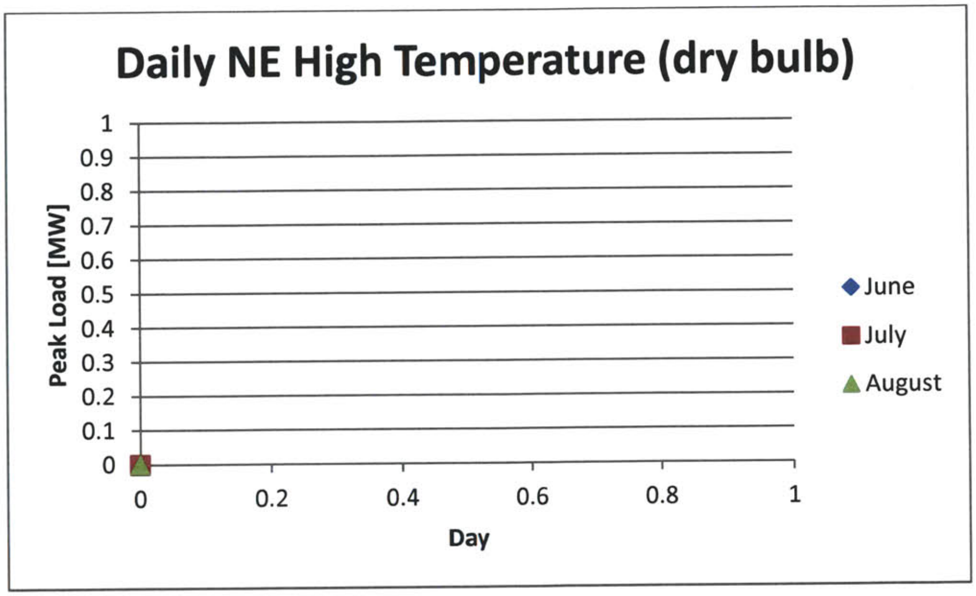

Figure 43: Comparison of June, July, and August 2010 daily high temperatures

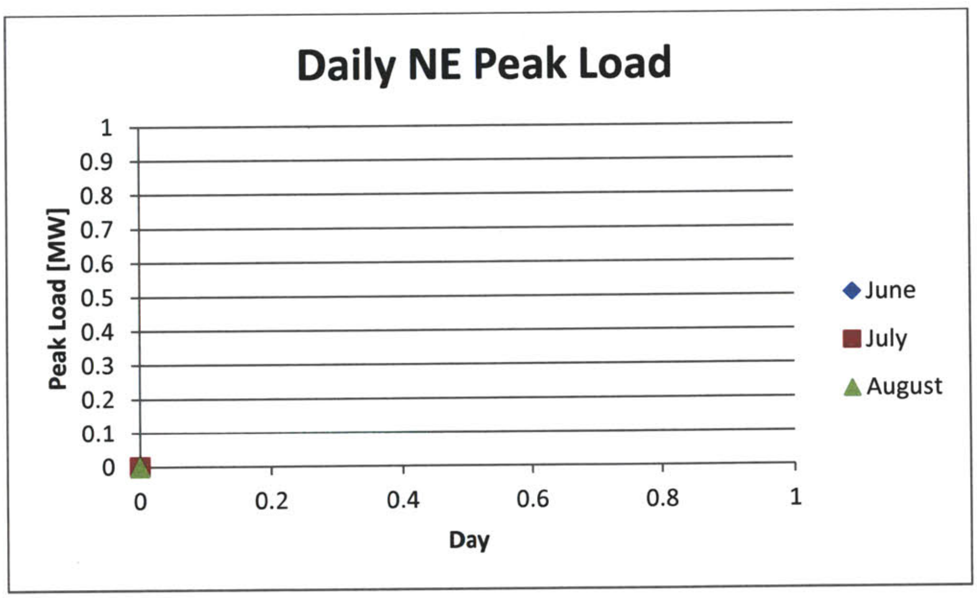

Figure 44: Comparison of June, July, and August 2010 daily peak loads

Though it is difficult to ascertain the underlying reason that demand bids in August are different than demand bids in June and July, we can at least examine more closely in what way the bids are different. In order to make such an examination, we again plot the feature vectors representing the clusters shown in Figure 42, without their corresponding demand clusters, in Figure 45. Here we can see that while in both the June/July and the August subperiods nighttime demand bid quantity is lower than daytime demand bid quantity, the overall demand bid quantity during hours in August are lower than the demand bid quantity for hours in June/July. Note that the feature vector representing demand bids during August daytime hours is more closely matched to the June/July nighttime hours than it is to the June/July daytime hours. This is another way of showing the same result as we saw in Figure 37, but with a bit more information provided. Here, in addition to the discrepancy between June/July and August, we see that the reason August daytime hours are clustered with June/July nighttime hours is that overall demand bid quantity is lower in August, and the August daytime demand bids are shifted such that they more closely match June/July nighttime bids than June/July daytime bids.

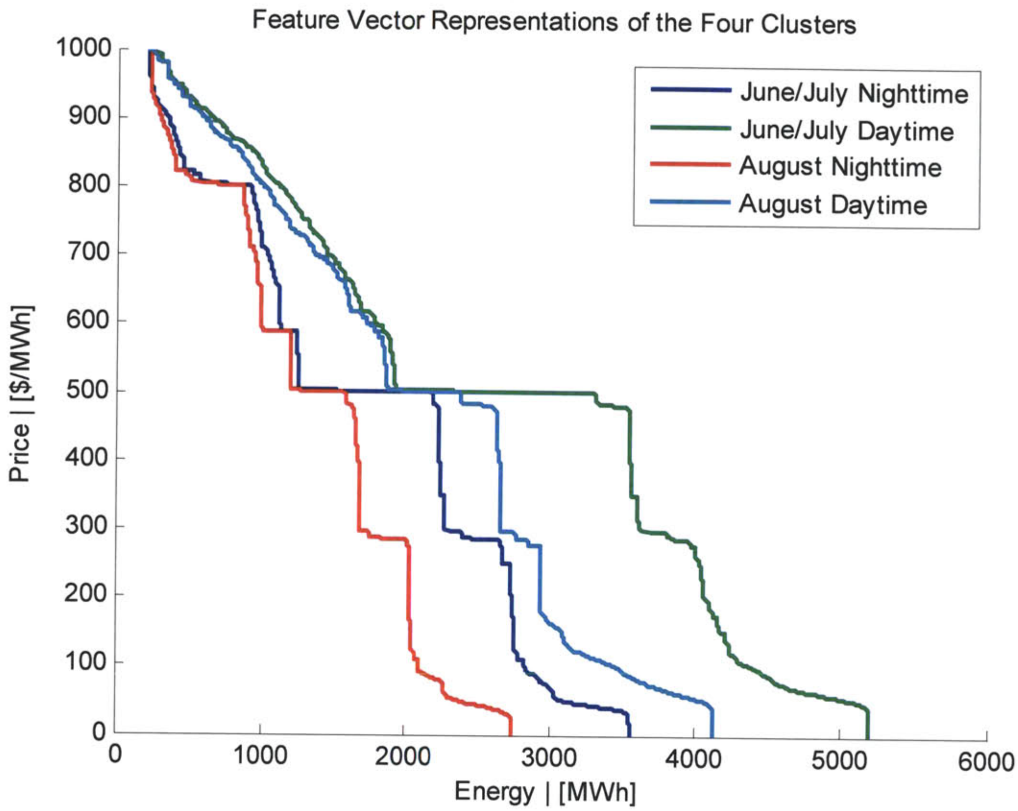

Figure 45: Feature vectors representing demand bid clusters in the four chosen subperiods

Having settled on the choice of subperiods for our case study, in the next section we turn to a discussion of the demand elasticity scenarios in New England to be analyzed and the results of the analysis. Finally, we will discuss these results and the conclusions which should be drawn by regulators about the future of reliability and capacity planning in the presence of demand elasticity.

4.3 Description of Scenarios

Two scenarios of demand response penetration in New England are now developed to illustrate the impact of demand elasticity on reliability metrics, and to spur discussion on the continuing need for new regulatory tactics to deal with this changing role of demand in electricity markets.

- Demand elasticity today. This is the straightforward application of the PPC model to the New England power system as described in the previous sections.
- Demand elasticity in the future. This second scenario of greater demand elasticity reflects a future where demand response continues to become more integral to system operations. The level of penetration chosen for the future scenario is based on the FERC's 2009 National Assessment of Demand Response Potential.

In order to illustrate the impact of ignoring demand elasticity on reliability metrics, we will run the PPC model twice for each of these scenarios: once considering demand elasticity as fictitious generators in the PPC model as described in Section 3.1.2, and once ignoring the effect of demand elasticity on reliability metrics by running only the basic thermal PPC model without considering demand elasticity.

Scenario 1: Demand elasticity today

Demand elasticity in New England today has been described throughout Section 4. To summarize, demand elasticity in the day-ahead market will be modeled in the PPC framework as fictitious generators. The quantity of this sort of demand elasticity ranges from 2500 MW to 5000 MW depending on the hour, and four subperiods to study using the modified PPC model were chosen based on application of the Neural Gas clustering algorithm (see Figure 42). Each subperiod is represented by a single feature vector elastic demand curve. Demand response programs in New England have been collectively modeled with 1900 MW of reserve-sensitive demand elasticity triggered when supply resources drop below 15% of total supply.

Scenario 2: Demand elasticity in the future

In the future, we assume the quantity of demand elasticity in New England will increase. The increase will be a combination of interruptible and price based demand response programs, as described in the National Assessment of Demand Response Potential (FERC, 2009). While this assessment does not provide *predictions* of the amount of increase, it does estimate the *potential* for demand response in New England.

Relevant results from the 2009 National Assessment of Demand Response Potential are shown in Table 6. Reduction potential for the New England region as a whole is not given explicitly in the assessment, but it is calculated here as the average of reduction potential in each of the New England states weighted by the contribution of each state to New England's total peak load.

Estimates are given in this assessment of demand response potential of several scenarios, including the two extreme cases shown in Table 6 (Business As Usual and Full Participation) as well as several intermediate scenarios of penetration. We will choose to use the Full Participation reduction potential in our PPC scenario of future demand response potential; unlike the National Assessment of Demand Response Potential, we are not representing the future in 2019 but rather a more distant future when demand elasticity becomes more prominent. In order to best illustrate our point, we choose to use the peak reduction level which the FERC reports is possible but not necessarily likely by the year 2019.

State/Region	Business As Usual	Full Participation	Peak Load
Connecticut	16%	29%	7524 MW
Maine	16%	24%	2812 MW
Massachusetts	7%	17%	12695 MW
New Hampshire	3%	13%	2539 MW
Rhode Island	7%	16%	1785 MW
Vermont	7%	13%	1085 MW
New England	9.9%	20.29%	28440 MW

Table 6: Demand response peak reduction potential in 2019 (FERC, 2009)

The PPC scenario of demand elasticity in the future will assume today's generators and loads while increasing the fraction of demand contributing to elasticity of the demand curve. Rather than reflecting the changes the system might undergo in the future such as increasing load and new generating units added, all of which would contain significant uncertainty, this is a scenario of increased demand elasticity in today's system. Since demand elasticity is likely to increase in the future regardless of the other changes, we are capturing the aspect of the future power system which is most relevant to our point: that reliability metrics, planning criteria, and definitions should be reconsidered.

Current interruptible demand response programs in NE total about 1900 MW, approximately 7% of annual peak load (which is roughly 28000 MW). As shown in Table 6, the National Assessment of Demand Response Potential estimates that in a 'full participation' scenario for the year 2019, reflecting the maximum potential of the region for demand response, the quantity of demand response in New England could reach 20% of system peak through a combination of price-based and reliability based programs. At today's system peak of approximately 28000 MW, demand response totaling 20% of system peak would be roughly 5700 MW, three times the 1900 MW currently enrolled in New England demand response programs. Our future scenario will therefore include 5700 MW of demand response in New England.

Given that changes in New England demand response programs will be implemented following confirmation of FERC order 745, it is likely that a greater fraction of the demand response increase will come through price based programs than reliability programs. Additionally, it is possible that some of the 1900 MW currently participating in the interruptible programs will switch to a price-based demand response. In our future scenario we will divide the 5700 MW of total reduction potential into 2500 MW of interruptible, reserve-sensitive demand and 3200 MW of price responsive demand.

Since demand-side bids in the day-ahead market are not 'demand response', but rather demand elasticity, these bids are not considered to be part of the demand response programs in New England. In the National Assessment of Demand Response Potential, demand bids are not reflected in the percent peak load reduction numbers; the assessment also does not say anything about whether the quantity of demand bids are likely to change. We will therefore leave these bids unchanged, but introduce new bids totaling 3200 MW.

There is little basis to predict prices and quantities of individual demand response in the future. Large customers already participate in demand response programs, and the National Assessment of Demand Response Potential shows that much of the demand response potential rests with smaller customers. This would suggest that demand bids would be small in quantity. However, aggregators are likely to bring together many customers so that demand participation would be represented by larger quantities, more manageable for system operators. Current New England rules set a minimum of 100 kW for participation in the Real-Time Price Response Program. It would be reasonable to assume that future demand will participate in price-based programs as groups of 100 kW.

As long as we assume in the PPC model that demand response is available 100% of the time (a forced outage rate of zero), then the size of demand bids is irrelevant to the reliability calculations of the PPC model. Demand bid prices (their place in the merit order) are also irrelevant. That is, LOLP and ENSE will not be affected whether there is one bid of 3200 MW or 3200 bids of 1 MW each, as long as we assume that the EFOR of these bids is 0. In our analysis we will indeed make this assumption. However, future work which considers forced outage rates of demand should also analyze the likely quantity and price distribution of bids in more detail.

4.4 Results of Scenario Analysis

We conducted four runs of the PPC model, twice for each of the two scenarios of demand elasticity in New England. Since it appears that New England does consider interruptible demand in its calculation of reliability measures, in all four scenarios we consider the interruptible demand. We change only whether the elastic portion of the demand curve is considered, including demand bids in the day-ahead market and future price-based demand response programs:

- Run 1: Considers the New England system with present levels of demand elasticity and interruptible demand. Interruptible demand is considered in the PPC model but price-based demand elasticity is not.
- Run 2: Considers the New England system with present levels of demand elasticity and interruptible demand. Both interruptible and price-based demand are considered in the PPC model.
- Run 3: Considers a future New England system with increased interruptible and price-based demand elasticity. Interruptible demand is considered in the PPC model but price-based demand elasticity is not.
- Run 4: Considers a future New England system with increased interruptible and price-based demand elasticity. Both interruptible and price-based demand elasticity are considered in the PPC model.

Each run considers the summer months of June, July, and August, and this timeframe of study is divided into four sub periods as described in Section 4.2.2. Figure 46 shows the PPC model convolution results for one of these sub periods, the nighttime hours of June and July (Run 2). We will first describe these results and use them to illustrate how the results from the four sub periods are combined into overall results for the run.

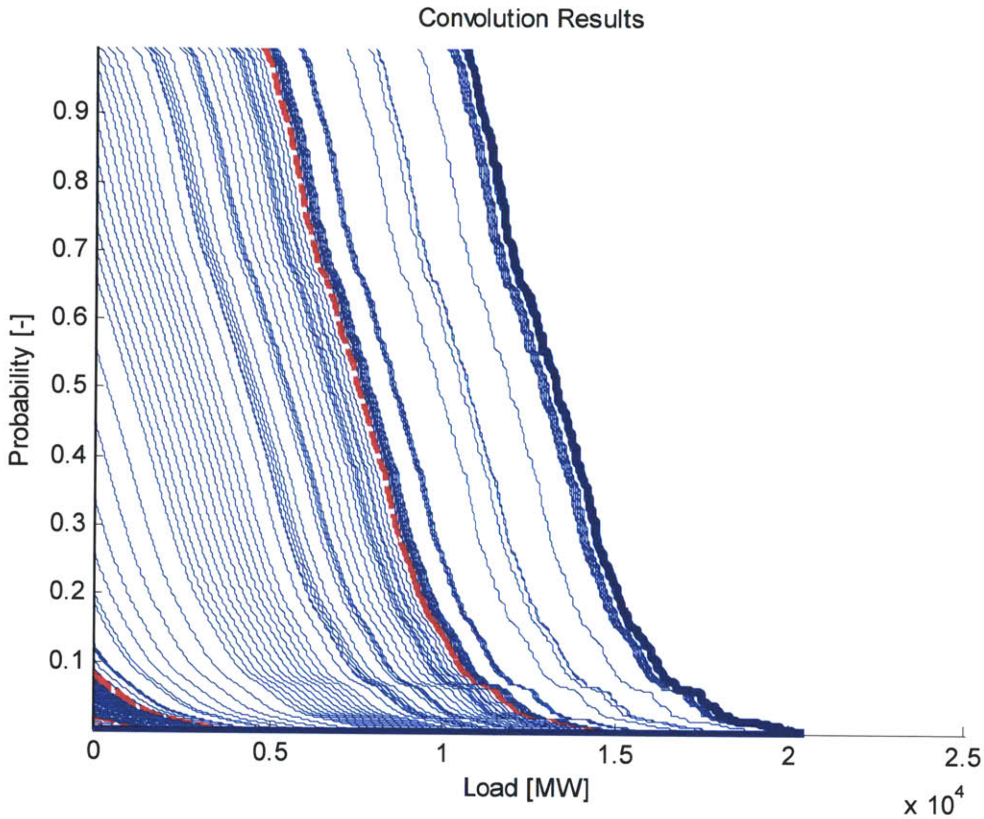

Figure 46: Region of PPC convolution results relevant to LOLP/ENSE, June/July nighttime hours

In Figure 46, we see the equivalent LCDF curves generated during the convolutions of successive generators (and fictitious generators) with the original LCDF representing system demand. The original LCDF is the line on the far right; successive generators' contributions to meeting demand are represented by the area between each line moving from right to left. Refer to Section 3.1 for a more complete description of PPC results.

Note that the blue lines represent real generators and red lines represent fictitious generators representing elastic demand. Recall that graphically, the LOLP is the intersection of the last LCDF (the LCDF farthest to the left) with the vertical axis. Clearly, the LOLP is very small in this example; it is impossible to even see the point of this intersection at the resolution shown. We have calculated the LOLP in this sub period to be 2.78E-26.

We can get a better graphical idea of system reliability by expanding our view of the convolution results to include negative load values, as shown in Figure 47. Equivalent LCDF curves which are primarily to the left of the vertical axis represent relatively expensive generators which are unlikely to be needed in meeting system load because cheaper generators, represented by the LCDF curves to the right of the vertical axis, come first in the merit order. Notice that the majority of fictitious generators, i.e. demand side bids, fall on the left of the vertical axis. In this sub period, demand reduction bids rarely clear the market. In other words, these bidders normally are supplied with energy rather than foregoing that energy because it is too expensive. Qualitatively, the larger the area of LCDF curves to the left of the vertical axis, the more reliable the system and the smaller the LOLP result.

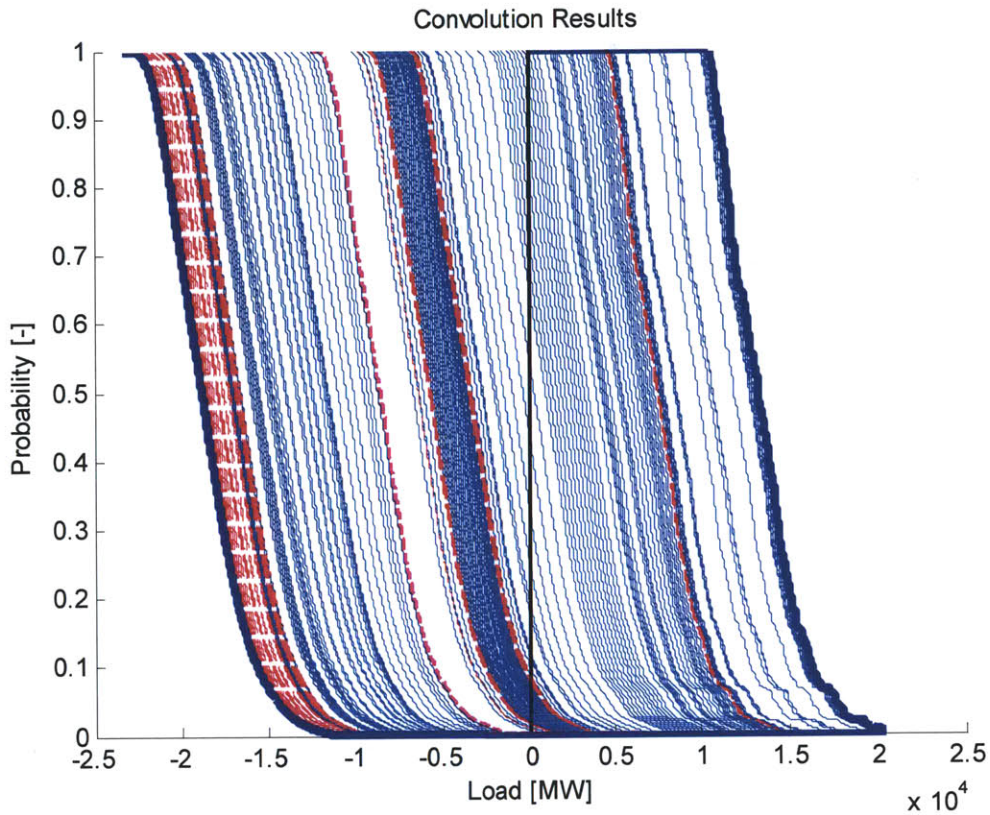

Figure 47: Convolution results of PPC model, June/July nighttime hours

Results from another sub period, the daytime hours in June and July, are shown in Figure 48. Here we can see that the area to the left of the vertical axis is reduced, meaning that there is a slightly higher LOLP in this sub period. The LOLP is still extremely small at 2.61e-12. However, we can see that there is an increased chance that some demand bids will clear the market, though the bulk of the very expensive bids are still very low probability.

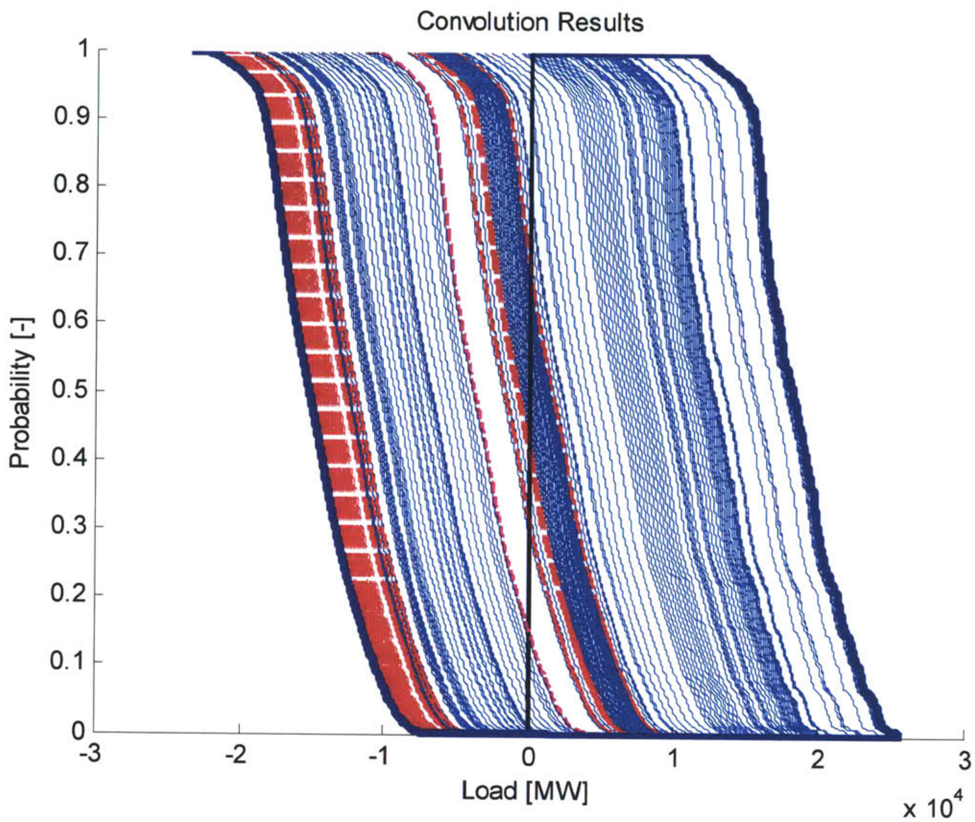

Figure 48: Convolution results of PPC model, June/July daytime hours

A summary of the calculation of the LOLP for Run 1 is shown in Table 7. The LOLP for each sub period is calculated as described above. Each of these LOLP values is scaled by the fraction of the total hours which are within that sub period and the sum of these scaled LOLPs is the overall LOLP for the run.

Metric	Jun/Jul Night	Jun/Jul day	Aug Night	Aug Day	Total
LOLP	**2.78E-26**	**2.61E-12**	**4.66E-23**	**1.38E-13**	**1.42E-12**
Hours in Sub Period	**488**	**1403**	**279**	**465**	**2635**

Table 7: Calculation of LOLP for Run 1

The LOLP and ENSE results for all four runs are presented in Table 8; the result from Table 7 can be seen as the LOLP result for Run 2. Moving across the results in Table 8 from left to right, we can see that in the scenario for today's demand elasticity, both LOLP and ENSE are much smaller when we consider demand elasticity than when we do not consider demand elasticity, indicating a higher level of reliability. The actual system is the same in both cases, but not accounting for demand elasticity makes it appear much less reliable than it actually is. The same is true in the future scenarios; considering elasticity makes the system appear much more reliable as reflected through traditional reliability metrics of LOLP and ENSE. The discrepancy becomes more pronounced in the future scenario, when demand elasticity increases.

The small decrease in LOLP from Run 1 to Run 3 is due to the increased reserve-based demand participation; recall that the Today scenario included 1900MW of reserve-based demand response while the future scenario included 2500MW of reserve-based demand response.

Metric	Today	Best Case - Present	Future	Best Case - Future
	Run 1: Do not consider Elasticity	Run 2: Consider Elasticity	Run 3: Do not consider Elasticity	Run 4: Consider Elasticity
LOLP	9.19E-6	1.42E-12	1.80E-6	5.69E-21
ENSE	4.69	4.48E-7	0.84	1.33E-15

Table 8: Comparison of reliability metrics in different scenarios of demand elasticity

As suggested in Rodilla & Batlle (2011), the Value of Non-Purchased Energy could be used as a metric to assess the performance of markets to complement the use of traditional reliability metrics such as LOLP and ENSE. Whereas LOLP and ENSE are metrics which are based on the traditional definition of reliability which assumes that demand is a fixed quantity to be fulfilled by suppliers, regardless of cost, the VNPE is a whole market performance metric not related to the traditional definition of reliability. As such, it could be a valuable complement to these traditional metrics in the transition to higher penetrations of demand elasticity in the future.

Risk analysis of the value of non-purchased energy for Run 2 and Run4 are shown in Figure 49 and Figure 50, respectively. The VNPE concept is dependent upon consideration of demand elasticity in the PPC model; therefore there are no VNPE results for Run 1 and Run 3. To interpret these results, it may be helpful to refer to Figure 19 on page 39. Figure 19 shows a theoretical VNPE probability distribution and shows how it can be represented by a number of metrics such as the mean, the VaR, or CVaR.

The same concept applies to Figure 49, but the probability distribution resulting from the PPC model is not as easy to interpret. The distribution analogous to the distribution in Figure 19 is labeled 'Probability Distribution'. It represents the probability of the system having various levels of VNPE over the timeframe of study. Unlike the smooth probability distribution in Figure 19, the VNPE here in the New England power system as modeled might take only a few values and the VNPE probability distribution is choppy. It is easier to see the shape of the cumulative distribution function and relate this to the mean value, or the Expected Value of Non-Purchased Energy (EVNPE). The VaR95 and CVaR95 thresholds indicate the VNPE at which there is a 95% chance of having a VNPE below; CVaR95 is slightly more conservative than VaR95. The precise choice of metric to represent the VNPE distribution function is not as important as the concept of incorporating some measure not just of the probability of losing load or energy, but of the value of the energy or load lost. Incorporating such a metric would improve the comprehensiveness of regulators' understanding of market behavior and system reliability.

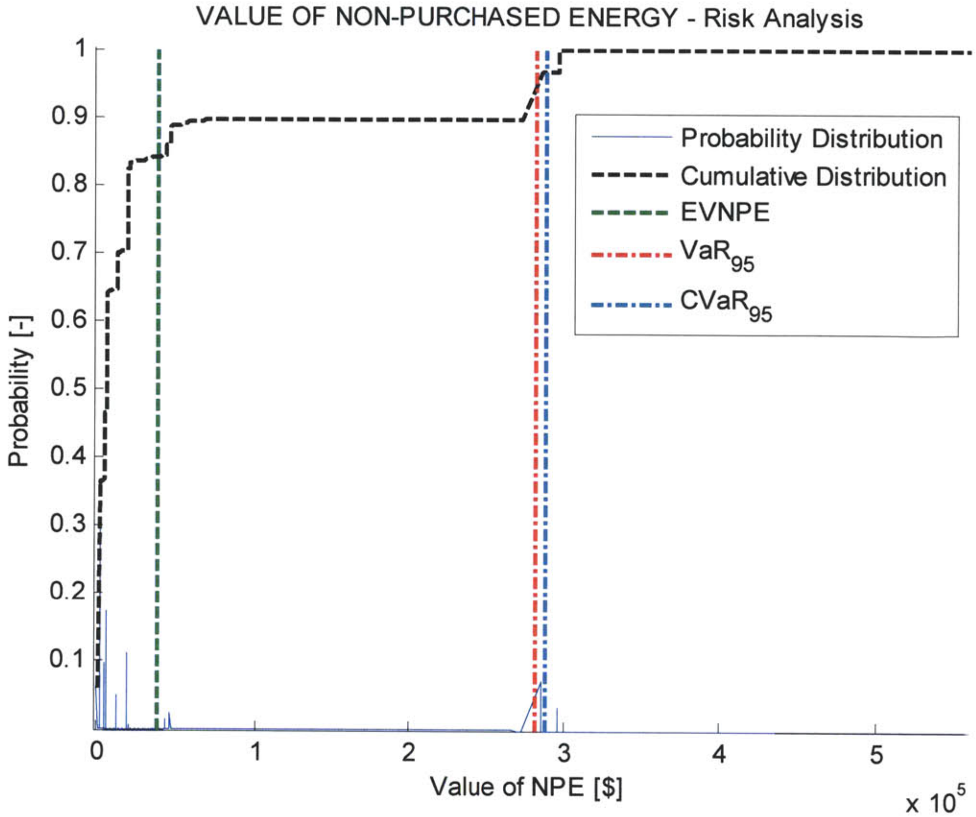

Figure 49: VNPE risk analysis for today's demand elasticity (Run 2)

The VNPE distribution function for the model of future demand elasticity in Figure 50 is very similar to the VNPE distribution function for today's demand elasticity. We can see an increase in the VaR95 and CVaR95 levels, reflecting the additional demand side bids in the scenario of increased demand elasticity. The EVNPE remains the same because this is a discrete probability distribution, and despite the possibility of higher VNPE with additional demand bids the expected VNPE – the level it is most likely to take on - remains at the same discrete level as it was in the scenario of less demand elasticity.

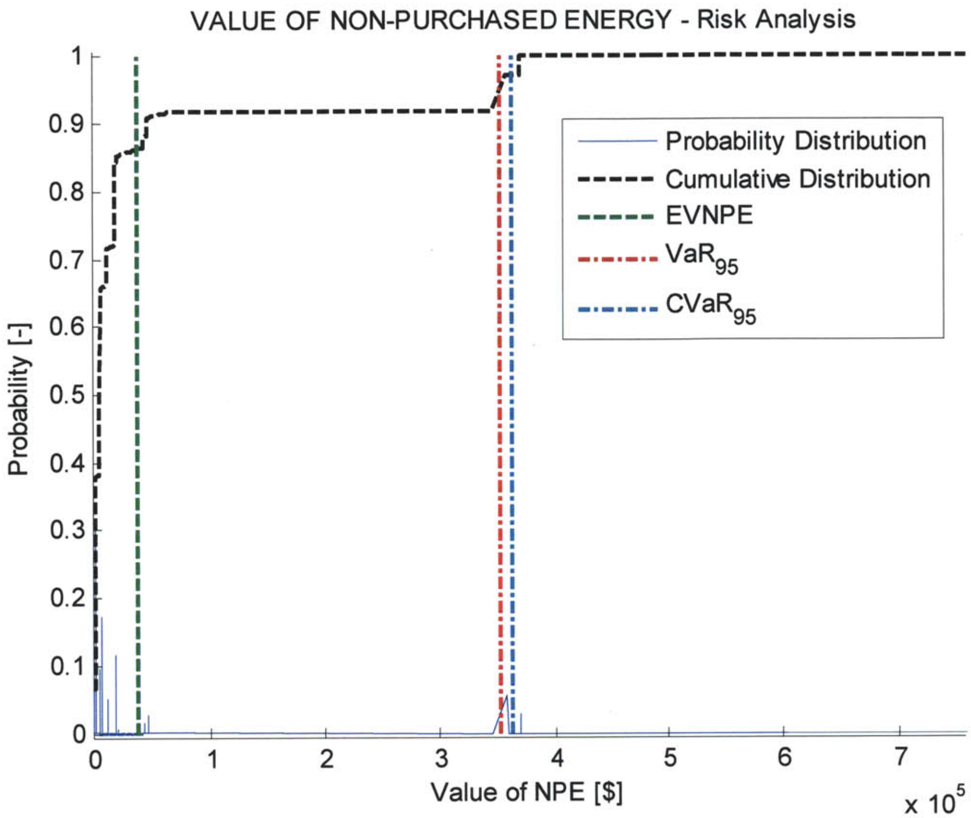

Figure 50: VNPE risk analysis for future demand elasticity (Run 4)

5 Conclusion

When electricity industry reforms began more than two decades ago, it was widely hoped that the central planning role of the regulator would decrease. In practice, short-term electricity markets are generally not able to achieve what regulators consider as adequate long-term security of supply (Rodilla & Batlle, 2010). Regulators and system operators have found it necessary to continue oversight of long-term expansion planning. Since in principle system operators are not supposed to own generation[6] or explicitly determine the capacity (and technology) to be built, the methods available are indirect but still play a key role. For instance, in the case around which this thesis is built, the New England electricity market, the independent system operator is responsible for evaluating future system capacity needs to guarantee a certain level of reliability. So to some extent, the New England ISO shapes future capacity expansion of the power system by guaranteeing a minimum amount. This responsibility is carried out through the Forward Capacity Market mechanism.

However, as we have pointed out throughout this thesis, increasingly active participation by loads in electricity markets makes traditional methods of capacity planning outdated. While long known to be beneficial from the perspective of economic efficiency, market maturity and technology development have only recently reached a point which enables a significant portion of demand side engagement. As evidenced by the 2009 National Assessment of Demand Response Potential, the amount of responsive demand today is only a fraction of what it could be in the future.

A future increase of active demand participation in short- and long-term markets will require regulators to rethink some fundamental principles of system operations and planning. One area in particular which will require attention is system reliability, where current planning criteria and reliability metrics are based on an interpretation of reliability which excludes the concept of demand response.

In Section 2.1.3, we discussed past criticisms of the ubiquitous LOLE reliability planning standard of one day in ten years. In addition to the likelihood that this criterion is on its face too conservative – in other words, that customers would prefer to have reduced payments for electricity even with the resulting decline in reliability – we also note that the one day in ten years criterion is applied in a conservative manner, meaning that in practice planners ensure that the system is even more reliable than one day in ten years. Our analysis of the New England power system shows that excluding demand elasticity from reliability planning is another specific way in which reliability planners might be achieving overly conservative reliability results. Table 8 contains PPC model results both considering and not considering demand elasticity, and highlights that ignoring demand will result in overly conservative estimates of system reliability.

However, this is only a superficial observation within the current framework of reliability planning based on reliability definitions which assume a fixed level of demand unresponsive to changing market prices. In the future, as demand becomes a more active participant in

[6] This is not always the case. For instance, the Swedish Transmission System Operator bought a number of old generation facilities to keep them as last resort reserve. This sort of action is very controversial, since it could turn into a tool with which the TSO can interfere in the short-term market, affecting schedules, prices and therefore the income of market agents.

markets, the need to develop new tools and metrics to account for demand responsiveness will become more urgent. One of the tools which has in the past and could in the future play a greater role in the transition from a mindset of central planning to one based more purely on markets is the one which has been explained in this thesis: a PPC model incorporating demand elasticity as fictitious generating units.

A sub-problem of the PPC model is the question of how to properly deal with the time dimension. The PPC framework requires us to consider a single set of generators and a single probability distribution representing the probability of a given load level. This becomes problematic when we consider demand bids which change hourly, and when we have incomplete information about the true capabilities of generators which also changes by the hour. In this thesis, we have dealt with the time-varying nature of demand in the PPC model by using a Neural Gas clustering algorithm to divide the time scope of study into sub periods, and representing similar sets of demand bids by single feature vector demand curves.

The Value of Non-Purchased Energy is one metric which could play a complementary role in reliability planning. We do not suggest abandoning traditional methods of reliability planning, at least not in the short term; we only point out that, in order to best serve electricity customers in the market environment, it will be necessary for regulators and by extension system planners to develop a view of reliability inclusive of demand response.

More work and a comprehensive stakeholder process is required to develop an approach to the transition from a deeply ingrained traditional reliability mentality to a balanced view of reliability which incorporates demand responsiveness and market efficiency measures. It is hoped that the work in this thesis will spur more discussion on this topic in the context of New England and other U.S. power systems.

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7 Appendix A: Generator List for PPC Model

Data and approximations used to represent the New England system's generators in the PPC model. The key to the unit type code follows the data.

This data is explained in section 4.2.1 of the text.

Generator Name	Unit Type	EFORd	Variable Price ($)	SSCC (MW)
MANCHESTER 10/10A CC	CC	0.06	40	149.00
MANCHESTER 11/11A CC	CC	0.06	40	149.00
MANCHESTER 9/9A CC	CC	0.06	40	149.00
CDECCA	CC	0.06	40	55.25
ALTRESCO	CC	0.06	40	151.44
AMOSKEAG	HD	0.07	0	16.78
GULF ISLAND COMPOSITE	HW	0.04	0	32.97
ASCUTNEY GT	G	0.10	60	
AYERS ISLAND	HD	0.07	0	8.47
AZISCOHOS HYDRO	HD	0.07	0	6.81
BAR HARBOR DIESELS 1-4	D	0.07	400	5.95
BELLOWS FALLS	HD	0.07	0	48.54
BERLIN 1 GT	G	0.10	60	34.83
BRIDGEPORT HARBOR 2	F	0.07	120	130.50
BRIDGEPORT HARBOR 3	F	0.07	120	383.43
BRIDGEPORT HARBOR 4	G	0.10	60	14.36
BOLTON FALLS	HD	0.07	0	3.33
BOOT MILLS	HD	0.07	0	6.73
BRAYTON PT 1	F	0.07	120	243.46
BRAYTON PT 2	F	0.07	120	244.00
BRAYTON PT 3	F	0.07	120	612.00
BRAYTON PT 4	F	0.07	120	435.00
BRAYTON DIESELS 1-4	D	0.07	400	9.91
BRANFORD 10	G	0.10	60	15.84
J. COCKWELL 1	PS	0.03	100	284.31
J. COCKWELL 2	PS	0.03	100	284.64
POTTER DIESEL 1	D	0.07	400	2.25
BURLINGTON GT	G	0.10	60	18.45
CANAL 1	F	0.07	120	547.06
CANAL 2	F	0.07	120	545.13
CAPE GT 4	G	0.10	60	15.93
CAPE GT 5	G	0.10	60	15.82
CATARACT EAST	HD	0.07	0	7.78
COS COB 10	G	0.10	60	19.03
COS COB 11	G	0.10	60	18.72
COS COB 12	G	0.10	60	19.08
CLEARY 9/9A CC	CC	0.06	40	104.93

CLEARY 8	F	0.07	120	25.85
COBBLE MOUNTAIN	HW	0.04	0	
COMERFORD	HW	0.04	0	142.84
MERRIMACK CT1	G	0.10	60	16.83
MERRIMACK CT2	G	0.10	60	16.80
DARTMOUTH POWER	CC	0.06	40	62.16
DERBY DAM	HD	0.07	0	7.05
DEERFIELD 5	HD	0.07	0	13.70
DOREEN	G	0.10	60	15.96
DEVON 10	J	0.10	200	14.41
DEVON 11	G	0.10	60	29.30
DEVON 12	G	0.10	60	29.23
DEVON 13	G	0.10	60	29.97
DEVON 14	G	0.10	60	29.70
EASTMAN FALLS	HD	0.07	0	5.58
ELLSWORTH HYDRO	HW	0.04	0	9.10
EASTPORT DIESELS 1-3	D	0.07	400	2.20
FIFE BROOK	HD	0.07	0	6.09
FLORENCE 1 CG	G	0.10	60	
FLORENCE 2 CG	G	0.10	60	
FRAMINGHAM JET 1	G	0.10	60	10.89
FRAMINGHAM JET 2	G	0.10	60	9.91
FRAMINGHAM JET 3	G	0.10	60	11.42
FRANKLIN DRIVE 10	G	0.10	60	15.42
FRONT STREET DIESELS 1-3	D	0.07	400	8.29
GREAT LAKES - MILLINOCKET	HW	0.04	0	31.68
GORGE 1 DIESEL	G	0.10	60	
GORHAM	HD	0.07	0	1.96
HARRIS 1	HW	0.04	0	16.79
HARRIS 2	HW	0.04	0	34.87
HARRIS 3	HW	0.04	0	34.21
HARRIMAN	HW	0.04	0	41.04
HOLYOKE 6/CABOT 6	F	0.07	120	9.21
HOLYOKE 8/CABOT 8	F	0.07	120	9.22
HIRAM	HD	0.07	0	11.19
COVANTA WEST ENFIELD	F	0.07	120	20.46
COVANTA JONESBORO	F	0.07	120	20.23
IPSWICH DIESELS	D	0.07	400	10.24
JACKMAN	HW	0.04	0	3.55
JOHNSTON LANDFILL	D	0.07	400	11.96
KENDALL JET 1	G	0.10	60	18.00
LAWRENCE HYDRO	HD	0.07	0	7.01
LENERGIA ENERGY CENTER	CC	0.06	40	74.64
AEI LIVERMORE	F	0.07	120	34.70
LOST NATION	G	0.10	60	14.07
DEERFIELD 2/LWR DRFIELD	HD	0.07	0	19.28
L STREET JET	G	0.10	60	16.03
MARBLEHEAD DIESELS	D	0.07	400	5.00

MARSHFIELD 6 HYDRO	HW	0.04	0	4.66
M STREET JET	G	0.10	60	
MCINDOES	HD	0.07	0	10.07
J C MCNEIL	F	0.07	120	52.00
MEDWAY DIESELS 1-4	D	0.07	400	4.30
MIDDLETOWN 10	G	0.10	60	
MIDDLETOWN 1	F	0.07	120	
MIDDLETOWN 2	F	0.07	120	117.00
MIDDLETOWN 3	F	0.07	120	236.00
MIDDLETOWN 4	F	0.07	120	400.00
MILLSTONE POINT 2	N	0.02	0	875.82
MILLSTONE POINT 3	N	0.02	0	225.00
MILFORD POWER	CC	0.06	40	149.00
MERRIMACK 1	F	0.07	120	112.50
MERRIMACK 2	F	0.07	120	338.38
MONTVILLE 10 and 11	D	0.07	400	5.30
MONTVILLE 5	F	0.07	120	81.00
MONTVILLE 6	F	0.07	120	407.40
MONTY	HD	0.07	0	28.00
MOORE	HW	0.04	0	189.98
MASS POWER	CC	0.06	40	238.26
MT TOM	F	0.07	120	142.88
MYSTIC 7	F	0.07	120	577.59
MYSTIC JET	G	0.10	60	8.59
NEA BELLINGHAM	CC	0.06	40	277.62
NEWINGTON 1	F	0.07	120	400.20
NEW HAVEN HARBOR	F	0.07	120	447.89
NORWICH JET	G	0.10	60	15.26
NORWALK HARBOR 1	F	0.07	120	162.00
NORWALK HARBOR 2	F	0.07	120	168.00
NORWALK HARBOR 10 (3)	G	0.10	60	11.93
OCEAN ST PWR GT1/GT2/ST1	CC	0.06	40	270.90
OCEAN ST PWR GT3/GT4/ST2	CC	0.06	40	270.18
PAWTUCKET POWER	CC	0.06	40	59.94
PILGRIM NUCLEAR POWER STATION	N	0.02	0	677.28
PINETREE POWER	F	0.07	120	16.15
POTTER 2 CC	CC	0.06	40	73.93
RESCO SAUGUS	F	0.07	120	32.28
RUTLAND 5 GT	G	0.10	60	8.41
SALEM HARBOR 1	F	0.07	120	79.75
SALEM HARBOR 2	F	0.07	120	77.96
SALEM HARBOR 3	F	0.07	120	149.81
SALEM HARBOR 4	F	0.07	120	436.75
SEABROOK	N	0.02	0	46.88
SCHILLER 4	F	0.07	120	47.50
SCHILLER 5	F	0.07	120	43.08
SCHILLER 6	F	0.07	120	47.94
SCHILLER CT 1	G	0.10	60	17.62

SEARSBURG	HD	0.07	0	4.76
SHEPAUG	HW	0.04	0	41.51
SHERMAN	HW	0.04	0	6.15
SHREWSBURY DIESELS	D	0.07	400	13.75
SKELTON	HD	0.07	0	19.70
SMITH	HD	0.07	0	11.68
SO. MEADOW 11	G	0.10	60	35.78
SO. MEADOW 12	G	0.10	60	37.70
SO. MEADOW 13	G	0.10	60	38.32
SO. MEADOW 14	G	0.10	60	36.75
SOMERSET JET 2	G	0.10	60	
STONY BROOK 2A	G	0.10	60	67.40
STONY BROOK 2B	G	0.10	60	65.30
STEVENSON	HW	0.04	0	8.31
BORALEX STRATTON ENERGY	F	0.07	120	45.02
S.D. WARREN-WESTBROOK	F	0.07	120	42.59
TORRINGTON TERMINAL 10	G	0.10	60	15.64
TUNNEL 10	G	0.10	60	17.00
VERGENNES 5 and 6 DIESELS	D	0.07	400	3.94
VERNON	HD	0.07	0	32.00
VT YANKEE NUCLEAR PWR STATION	N	0.02	0	604.25
WATERS RIVER JET 1	G	0.10	60	16.05
WATERS RIVER JET 2	G	0.10	60	30.51
WATERBURY 22	HW	0.04	0	5.00
WEST ENFIELD	HD	0.07	0	6.63
WESTON	HD	0.07	0	13.20
WHITE LAKE JET	G	0.10	60	17.45
WILDER	HW	0.04	0	41.16
WILLIAMS	HD	0.07	0	14.90
WMI MILLBURY 1	F	0.07	120	39.81
WEST MEDWAY JET 1	G	0.10	60	30.76
WEST MEDWAY JET 2	G	0.10	60	34.73
WEST MEDWAY JET 3	G	0.10	60	35.44
WOODLAND ROAD	G	0.10	60	15.81
WEST SPRINGFIELD 10	G	0.10	60	17.14
WEST SPRINGFIELD 3	F	0.07	120	94.28
WYMAN HYDRO 1	HW	0.04	0	27.36
WYMAN HYDRO 2	HW	0.04	0	29.87
WYMAN HYDRO 3	HW	0.04	0	25.73
YARMOUTH 1	F	0.07	120	50.66
YARMOUTH 2	F	0.07	120	51.13
YARMOUTH 3	F	0.07	120	115.17
YARMOUTH 4	F	0.07	120	603.23
ROCHESTER LANDFILL	G	0.10	60	1.87
SIMPSON G LOAD REDUCER	HD	0.07	0	1.38
ROCKY RIVER	PS	0.03	100	29.35
BONNY EAGLE/W. BUXTON	HD	0.07	0	16.15
HARRIS 4	HW	0.04	0	1.44

MESSALONSKEE COMPOSITE	HD	0.07	0	3.04
NORTH GORHAM	HD	0.07	0	1.60
SHAWMUT	HD	0.07	0	9.50
GARVINS/HOOKSETT	HD	0.07	0	12.48
LOWER LAMOILLE COMPOSITE	HW	0.04	0	15.80
MIDDLEBURY COMPOSITE	HW	0.04	0	6.60
N. RUTLAND COMPOSITE	HW	0.04	0	5.20
MIDDLESEX 2	HD	0.07	0	1.55
LEWISTON CANAL COMPOSITE	HD	0.07	0	
GOODWIN DAM	HD	0.07	0	3.00
TOUTANT	HD	0.07	0	0.25
SANDY HOOK HYDRO	HD	0.07	0	0.11
BEEBE HOLBROOK	HD	0.07	0	0.21
ENOSBURG 2 DIESEL	D	0.07	400	0.78
STERLING DIESELS	D	0.07	400	0.33
CHEMICAL	HD	0.07	0	1.48
WARE COGEN - QF	F	0.07	120	
HG&E HYDRO/CABOT 1-4	HD	0.07	0	2.59
BARTON 1-4 DIESELS	D	0.07	400	0.62
CONCORD STEAM	F	0.07	120	
DIGHTON POWER LLC	CC	0.06	40	150.00
BUNKER RD #12 GAS TURB	G	0.10	60	2.35
BUNKER RD #13 GAS TURB	G	0.10	60	2.84
OAK BLUFFS	D	0.07	400	8.12
WEST TISBURY	D	0.07	400	5.57
BRIDGEPORT ENERGY 1	CC	0.06	40	460.95
BERKSHIRE POWER	CC	0.06	40	229.28
H.K. SANDERS	HW	0.04	0	1.74
STONY BROOK GT1A	CC	0.06	40	104.00
STONY BROOK GT1B	CC	0.06	40	100.00
STONY BROOK GT1C	CC	0.06	40	104.00
LOWELL COGENERATION PLANT	CC	0.06	40	27.18
MILLENNIUM	CC	0.06	40	325.79
MAINE INDEPENDENCE STATION	CC	0.06	40	488.28
ESSEX DIESELS	D	0.07	400	7.22
TIVERTON POWER	CC	0.06	40	244.64
RUMFORD POWER	CC	0.06	40	244.94
ANP-BLACKSTONE ENERGY 1	CC	0.06	40	223.63
ANP-BLACKSTONE ENERGY 2	CC	0.06	40	215.87
BUCKSPORT ENERGY 4	G	0.10	60	130.40
LAKE ROAD 1	CC	0.06	40	245.79
LAKE ROAD 2	CC	0.06	40	251.21
LAKE ROAD 3	CC	0.06	40	248.01
WALLINGFORD UNIT 1	G	0.10	60	42.30
WALLINGFORD UNIT 2	G	0.10	60	40.61
WALLINGFORD UNIT 3	G	0.10	60	42.30
WALLINGFORD UNIT 4	G	0.10	60	41.91
WALLINGFORD UNIT 5	G	0.10	60	40.72

MILFORD POWER 1	CC	0.06	40	253.61
MILFORD POWER 2	CC	0.06	40	253.09
ANP-BELLINGHAM 1	CC	0.06	40	236.37
ANP-BELLINGHAM 2	CC	0.06	40	237.02
GRS-FALL RIVER	G	0.10	60	3.11
MYSTIC 8	CC	0.06	40	690.92
SOUTHBRIDGE P&T QF U5	D	0.07	400	
MYSTIC 9	CC	0.06	40	690.92
GRANITE RIDGE ENERGY	CC	0.06	40	661.32
RISEP	CC	0.06	40	528.58
GROVETON COGEN U5	G	0.10	60	
WAUSAU COGEN U5	G	0.10	60	
NAEA NEWINGTON ENERGY, LLC	CC	0.06	40	506.24
KENDALL CT	CC	0.06	40	153.53
FORE RIVER-1	CC	0.06	40	688.30
WEST SPRINGFIELD GT-1	G	0.10	60	36.91
WEST SPRINGFIELD GT-2	G	0.10	60	37.44
GORGE 18 HYDRO-NEW	HD	0.07	0	2.16
VERGENNES HYDRO-NEW	HD	0.07	0	1.02
CHERRY 7	D	0.07	400	2.80
CHERRY 8	D	0.07	400	3.40
CHERRY 10	D	0.07	400	2.10
CHERRY 11	D	0.07	400	2.10
CHERRY 12	D	0.07	400	5.00
NECCO COGENERATION FACILITY	D	0.07	400	4.87
KENDALL STEAM 1	CC	0.06	40	13.57
KENDALL STEAM 2	CC	0.06	40	20.74
KENDALL STEAM 3	CC	0.06	40	19.12
GREAT LAKES - BERLIN	HD	0.07	0	5.00
GE LYNN EXCESS REPLACEMENT	G	0.10	60	
WATERSIDE POWER	G	0.10	60	71.70
FIEC DIESEL	D	0.07	400	1.64
PPL GREAT WORKS - RED SHIELD	F	0.07	120	
DEVON 15	G	0.10	60	46.85
MIDDLETOWN 12	G	0.10	60	
UNH POWER PLANT	G	0.10	60	3.11
SWANTON GT-1	G	0.10	60	18.17
SWANTON GT-2	G	0.10	60	18.11
WATERBURY GENERATION FACILITY	G	0.10	60	97.52
PIERCE STATION	G	0.10	60	75.83
JOHN STREET #3	D	0.07	400	2.00
JOHN STREET #4	D	0.07	400	2.00
JOHN STREET 5	D	0.07	400	2.01
MATEP (DIESEL)	D	0.07	400	17.78
MATEP (COMBINED CYCLE)	CC	0.06	40	45.61
VERSO COGEN 1	G	0.10	60	40.30
VERSO COGEN 2	G	0.10	60	40.30
VERSO COGEN 3	G	0.10	60	40.30

CORRIVEAU HYDROELECTRIC LLC	HD	0.07	0	0.05
MAT3	D	0.07	400	17.43
FITCHBURG LANDFILL	D	0.07	400	3.77
MONTAGNE FARM	D	0.07	400	0.19
COS COB 13	G	0.10	60	19.05
COS COB 14	G	0.10	60	19.61
WESTBROOK ENERGY CENTER G1	CC	0.06	40	255.03
WESTBROOK ENERGY CENTER G2	CC	0.06	40	254.38
INDECK ALEXANDRIA	F	0.07	120	13.88
NORTHFIELD MOUNTAIN 1	PS	0.03	100	
NORTHFIELD MOUNTAIN 2	PS	0.03	100	
NORTHFIELD MOUNTAIN 3	PS	0.03	100	
NORTHFIELD MOUNTAIN 4	PS	0.03	100	
AMERESCO NORTHAMPTON	D	0.07	400	
ETHAN ALLEN CO-GEN 1	F	0.07	120	
SBER ROYAL MILLS LLC	HD	0.07	0	
KLEEN ENERGY	CC	0.06	40	
COVANTA HAVERHILL - LF GAS	D	0.07	400	1.51
PINE TREE LFGTE	D	0.07	400	2.83
CABOT	HD	0.07	0	61.48
TURNERSFALLS	HD	0.07	0	6.40
NORDEN 1	D	0.07	400	1.96
NORDEN 2	D	0.07	400	1.95
NORDEN 3	D	0.07	400	1.94
CYTEC 1	D	0.07	400	1.93
CYTEC 2	D	0.07	400	1.94
CYTEC 3	D	0.07	400	1.94
NORWICH WWTP	D	0.07	400	2.00
ICE HOUSE PARTNERS, INC.	HD	0.07	0	0.07
UNION GAS STATION	HD	0.07	0	1.09
KIMB ROCKY RIVER PH2	CC	0.06	40	13.49
NEIGHBORHOOD ENERGY, LLC	D	0.07	400	
THOMAS A. WATSON UNIT #1	G	0.10	60	52.60
THOMAS A. WATSON UNIT #2	G	0.10	60	52.60
MORETOWN LFGTE	D	0.07	400	3.02
DARTMOUTH CT GENERATOR 3	G	0.10	60	20.92
CROSSROADS LANDFILL	D	0.07	400	2.29
DEVON 16	G	0.10	60	46.90
DEVON 17	G	0.10	60	46.90
DEVON 18	G	0.10	60	46.90
RAINBOW UNIT 1	HD	0.07	0	4.10
RAINBOW UNIT 2	HD	0.07	0	4.10
MIDDLETOWN 13	G	0.10	60	
MIDDLETOWN 14	G	0.10	60	46.90
MIDDLETOWN 15	G	0.10	60	46.90

Unit Type Key	
CC	Combined Cycle Total Unit
D	Internal Combustion Engine
F	Fossil
G	Combustion Gas Turbine
HD	Hydro-Conventional Daily Pondage or Run of River
HW	Hydro-Conventional Weekly
J	Jet Fuel
N	Nuclear
PS	Pumped Storage